Costa Rican Poverty Prediction Analysis

September 16, 2018

Costa Rican Poverty Predction
by: Jason Lin, Jason Lingle, and Jonathan Marin
9/16/2018

1 Business Understanding

The issue of poverty is an issue in even the wealthiest of countries such as the United States. While countries have their own way of providing support to individuals in need, the issue of identifying people with the most needs is always an issue. Many social programs have a hard time making sure the right people are given enough aid. It is especially difficult when a program focuses on the poorest segment of the population as they are unable to provide the income and expense records that are typically required for qualification.

In Latin America, a common method of verifying income qualification when income data is unavailable or unreliable is the Proxy Means Test (PMT). With PMT, agencies use a model that considers a family's observable household attributes like the material of their walls and ceiling, or the assets found in the home to classify them and predict their level of need. While this test is better at evaluating income needs over other methods, the accuracy of predicting income qualification remains a problem as the region's population grows and poverty declines.

With this backdrop, our team has selected a data set called the "Costa Rican Household Poverty Level Prediction" from Kaggle. The data set has been provided by the Inter-American Development Bank (IDB), which is the largest source of development financing for Latin American and Caribbean countries. The goal of the IDB in providing this data set is to get support in improving income qualification for some of the world's poorest families for social welfare assistance in Latin America. (https://www.kaggle.com/c/costa-rican-household-poverty-prediction). It is also their belief that new methods, beyond traditional econometrics, might be identified that could improve PMT performance. The dataset is a file with household characteristics from a sample of Costa Rican households from an unknown year. The dataset has observations for each member of the household, but the classification is done at the household level. The target is an ordinal variable indicating groups of income levels:

1 = extreme poverty 2 = moderate poverty 3 = vulnerable households 4 = non-vulnerable households

The goal is to use the household characteristics provided and possibly create new features to predict the income levels using classification. Since the test set does not have the target variable, we will test the accuracy by submitting our predicted results to Kaggle.

```
In [2]: import pandas as pd
        import numpy as np
```

```python
from pandasql import sqldf
import matplotlib.pyplot as plt
import seaborn as sns

sns.set()


train = pd.DataFrame(pd.read_csv("train.csv"))
test = pd.DataFrame(pd.read_csv("test.csv"))
```

2 Data Meaning Type

Variable Name	Definition	Variable Type
v2a1	Monthly rent payment	float
hacdor	=1 Overcrowding by bedrooms	bool
rooms	number of all rooms in the house	int
hacapo	=1 Overcrowding by rooms	bool
v14a	=1 has bathroom in the household	bool
refrig	=1 if the household has refrigerator	bool
v18q	owns a tablet	bool
v18q1	number of tablets household owns	int
r4h1	Males younger than 12 years of age	int
r4h2	Males 12 years of age and older	int
r4h3	Total males in the household	int
r4m1	Females younger than 12 years of age	int

Variable Name	Definition	Variable Type
r4m2	Females 12 years of age and older	int
r4m3	Total females in the household	int
r4t1	persons younger than 12 years of age	int
r4t2	persons 12 years of age and older	int
r4t3	Total persons in the household	int
tamhog	size of the household	int
tamviv	number of persons living in the household	int
escolari	years of schooling	int
rez_esc	Years behind in school	int
hhsize	household size	int
paredblolad	=1 if predominant material on the outside wall is block or brick	bool
paredzocalo	"=1 if predominant material on the outside wall is socket (wood zinc or absbesto"	bool
paredpreb	=1 if predominant material on the outside wall is prefabricated or cement	bool

Variable Name	Definition	Variable Type
pareddes	=1 if predominant material on the outside wall is waste material	bool
paredmad	=1 if predominant material on the outside wall is wood	bool
paredzinc	=1 if predominant material on the outside wall is zink	bool
paredfibras	=1 if predominant material on the outside wall is natural fibers	bool
paredother	=1 if predominant material on the outside wall is other	bool
pisomoscer	"=1 if predominant material on the floor is mosaic, ceramic, terrzo	bool
pisocemento	=1 if predominant material on the floor is cement	bool
pisoother	=1 if predominant material on the floor is other	bool
pisonatur	=1 if predominant material on the floor is natural material	bool
pisonotiene	=1 if no floor at the household	bool

Variable Name	Definition	Variable Type
pisomadera	=1 if predominant material on the floor is wood	bool
techozinc	=1 if predominant material on the roof is metal foil or zink	bool
techoentrepiso	"=1 if predominant material on the roof is fiber cement mezzanine	bool
techocane	=1 if predominant material on the roof is natural fibers	bool
techootro	=1 if predominant material on the roof is other	bool
cielorazo	=1 if the house has ceiling	bool
abastaguadentro	=1 if water provision inside the dwelling	bool
abastaguafuera	=1 if water provision outside the dwelling	bool
abastaguano	=1 if no water provision	bool
public	"=1 electricity from CNFL ICE ESPH/JASEC	bool
planpri	=1 electricity from private plant	bool
noelec	=1 no electricity in the dwelling	bool

Variable Name	Definition	Variable Type
coopele	=1 electricity from cooperative	bool
sanitario1	=1 no toilet in the dwelling	bool
sanitario2	=1 toilet connected to sewer or cesspool	bool
sanitario3	=1 toilet connected to septic tank	bool
sanitario5	=1 toilet connected to black hole or letrine	bool
sanitario6	=1 toilet connected to other system	bool
energcocinar1	=1 no main source of energy used for cooking (no kitchen)	bool
energcocinar2	=1 main source of energy used for cooking electricity	bool
energcocinar3	=1 main source of energy used for cooking gas	bool
energcocinar4	=1 main source of energy used for cooking wood charcoal	bool
elimbasu1	=1 if rubbish disposal mainly by tanker truck	bool
elimbasu2	=1 if rubbish disposal mainly by botan hollow or buried	bool

Variable Name	Definition	Variable Type
elimbasu3	=1 if rubbish disposal mainly by burning	bool
elimbasu4	=1 if rubbish disposal mainly by throwing in an unoccupied space	bool
elimbasu5	"=1 if rubbish disposal mainly by throwing in river	bool
elimbasu6	=1 if rubbish disposal mainly other	bool
epared1	=1 if walls are bad	bool
epared2	=1 if walls are regular	bool
epared3	=1 if walls are good	bool
etecho1	=1 if roof are bad	bool
etecho2	=1 if roof are regular	bool
etecho3	=1 if roof are good	bool
eviv1	=1 if floor are bad	bool
eviv2	=1 if floor are regular	bool
eviv3	=1 if floor are good	bool
dis	=1 if disable person	bool
male	=1 if male	bool
female	=1 if female	bool
estadocivil1	=1 if less than 10 years old	bool
estadocivil2	=1 if free or coupled uunion	bool
estadocivil3	=1 if married	bool

Variable Name	Definition	Variable Type
estadocivil4	=1 if divorced	bool
estadocivil5	=1 if separated	bool
estadocivil6	=1 if widow/er	bool
estadocivil7	=1 if single	bool
parentesco1	=1 if household head	bool
parentesco2	=1 if spouse/partner	bool
parentesco3	=1 if son/doughter	bool
parentesco4	=1 if stepson/doughter	bool
parentesco5	=1 if son/doughter in law	bool
parentesco6	=1 if grandson/doughter	bool
parentesco7	=1 if mother/father	bool
parentesco8	=1 if father/mother in law	bool
parentesco9	=1 if brother/sister	bool
parentesco10	=1 if brother/sister in law	bool
parentesco11	=1 if other family member	bool
parentesco12	=1 if other non family member	bool
idhogar	Household level identifier	string
hogar_nin	Number of children 0 to 19 in household	int
hogar_adul	Number of adults in household	int
hogar_mayor	# of individuals 65+ in the household	int
hogar_total	# of total individuals in the household	int

Variable Name	Definition	Variable Type
dependency	Dependency rate, calculated = (number of members of the household younger than 19 or older than 64)/(number of member of household between 19 and 64)	numeric
edjefe	years of education of male head of household, based on the interaction of escolari (years of education) head of household and gender, yes=1 and no=0	bool
edjefa	years of education of female head of household , based on the interaction of escolari (years of education) , head of household and gender, yes=1 and no=0	bool
meaneduc	average years of education for adults (18+)	int
instlevel1	=1 no level of education	bool
instlevel2	=1 incomplete primary	bool
instlevel3	=1 complete primary	bool

Variable Name	Definition	Variable Type
instlevel4	=1 incomplete academic secondary level	bool
instlevel5	=1 complete academic secondary level	bool
instlevel6	=1 incomplete technical secondary level	bool
instlevel7	=1 complete technical secondary level	bool
instlevel8	=1 undergraduate and higher education	bool
instlevel9	=1 postgraduate higher education	bool
bedrooms	number of bedrooms	int
overcrowding	# persons per room	int
tipovivi1	=1 own and fully paid house	bool
tipovivi2	"=1 own paying in installments	bool
tipovivi3	=1 rented	bool
tipovivi4	=1 precarious	bool
tipovivi5	"=1 other(assigned borrowed)"	bool
computer	=1 if the household has notebook or desktop computer	bool

Variable Name	Definition	Variable Type
television	=1 if the household has TV	bool
mobilephone	=1 if mobile phone	bool
qmobilephone	# of mobile phones	int
lugar1	=1 region Central	bool
lugar2	=1 region Chorotega	bool
lugar3	=1 region PacÃÂ■fico central	bool
lugar4	=1 region Brunca	bool
lugar5	=1 region Huetar AtlÃÂąntica	bool
lugar6	=1 region Huetar Norte	bool
area1	=1 zona urbana	bool
area2	=2 zona rural	bool
age	Age in years	int
SQBescolari	escolari squared	numeric
SQBage	age squared	numeric
SQBhogar_total	hogar_total squared	int
SQBedjefe	edjefe squared	int
SQBhogar_nin	hogar_nin squared	int
SQBovercrowding	overcrowding squared	float
SQBdependency	dependency squared	float
SQBmeaned	square of the mean years of education of adults (>=18) in the household	bool
agesq	Age squared	numeric

3 Data Quality

3.1 Missing Data (NaNs)

3.1.1 v2a1

This variable represents the Monthly Rent Payment. This may be null because there is no monthly rent payment as the subjet may own the house in full (variable:tipovivi1). When the home is owened in full, we populated the monthly payment as $0 instead of null. However, there are blanks still in train and test after doing so. It may be possible to build a prelimanary model to impute this with all the household and location characteristics that we already have, however, we have imputed the rest with the mean for the remaining nulls.

3.1.2 v18q1

This variable represents the number of people who own a tablet. This is a member level variable and the imputation of this will be handled by the aggregation to household level. We believe that the nulls here represent zero.

3.1.3 rez_esc

This variable represents the number of years a member is behind in school. This is a member level variable and the imputation of this will be hangled by the aggregation to household level. We beleive that the nulls here represent zero.

3.1.4 meaneduc

This variable represents the average years of education adults (18+) have. This is a household level variable. We have imputed this by taking the number of years of eduction from the head of household males/females.

3.1.5 SQBmeaned

This variable is the square of meaneduc which was null for the same columns that the meaneduc was null for. This was calculated by squaring the imputed meaneduc.

3.2 Outliers

The plan is to run a random forest model which is not sensitive to outliers. We will skip the outlier analysis for now. In feature modeling, it is easier to point out the outliers because of cross correlation and other factors.

3.3 Errors

The kaggle competition rules mentioned that the scoring only occurs on head of household, but member level data was provided. We have found member level data tied to households that had no head of household. These were excluded from the study since they will not be scored in the test set per kaggle rules.

Also, meaneduc and SQBmeaned were not populated even though we had information on head of household education.

3.4 Denormalization

Some variables of the dataset is at the member level and we are provided a key (variable: idhogar) that ties the member to the household. The target should be the same between all members of the household. If it is different, it is an error and we should use the head of household (variable: parentesco1) target. Note that the scoring on the test set within the kaggle competition is only done for heads of household. The member level was provided for additional feature engineering.

To overcome this, the plan would be to denormalize the data by head of household for both train and test for heads of household. Then, we will need to backfill the expected test set submission as it is expected to be submitted at the member level even though it is only scoring at the household level. We believe that we can leave the members that are not heads of household blank in the submission according to what was stated in the kaggle submission selection.

Data Attributes spreadsheet was created to show attributes and member level or household level. Variables were reviewed to assign each category appropriately. For some fields, it was a simple sum, but for others, we created bins for the column and then summed.

```
In [4]: #Find the Nulls
        null_columns=train.columns[train.isnull().any()]

        train[null_columns].isnull().sum()

Out[4]: v2a1       6860
        v18q1      7342
        rez_esc    7928
        dtype: int64

In [8]: # Update and Check to see we updated

        # There are 2156 null values for v2a1 (monthly mortgage payment).  After accounting fo
        #rent, we are left with 300 values that have nulls.  We can try to create a model

        train.loc[(train.tipovivi1 == 1),'v2a1'] = 0
        test.loc[(test.tipovivi1 == 1),'v2a1'] = 0


        train.loc[np.isnan(train["v18q1"]), 'v18q1'] = 0
        test.loc[np.isnan(test["v18q1"]), 'v18q1'] = 0

        train.loc[np.isnan(train["v18q1"]), 'v18q1'] = 0
        test.loc[np.isnan(test["v18q1"]), 'v18q1'] = 0


        train.loc[(train.dependency == "yes"),'dependency'] = 1
        train.loc[(train.dependency == "no"),'dependency'] = 0

        test.loc[(test.dependency == "yes"),'dependency'] = 1
        test.loc[(test.dependency == "no"),'dependency'] = 0
```

```
train.loc[(train.edjefe == "yes"),'edjefe'] = 1
train.loc[(train.edjefe == "no"),'edjefe'] = 0

test.loc[(test.edjefe == "yes"),'edjefe'] = 1
test.loc[(test.edjefe == "no"),'edjefe'] = 0



train.loc[(train.edjefa == "yes"),'edjefa'] = 1
train.loc[(train.edjefa == "no"),'edjefa'] = 0

test.loc[(test.edjefa == "yes"),'edjefa'] = 1
test.loc[(test.edjefa == "no"),'edjefa'] = 0


null_columns=train.columns[train.isnull().any()]

train[null_columns].isnull().sum()
```

Out[8]:

```
v2a1        949
rez_esc    7928
dtype: int64
```

In [12]:

```
#Denormalization

#Create subset dataframes for head of househoold for tain and test
train_head = train[['idhogar', 'parentesco1', 'Id', 'hhsize', 'v2a1', 'hacdor', 'rooms

train_head = train_head[train_head['parentesco1'] == 1]

test_head = test[['idhogar', 'parentesco1', 'Id', 'hhsize', 'v2a1', 'hacdor', 'rooms'

test_head = test_head[test_head['parentesco1'] == 1]

#Start the member level denormalization for train and test
train_member_agg = pd.DataFrame(sqldf("select  "
"idhogar, "
"sum(cast(v18q as int)) 'JM_Sum_of_Tablets', "
"sum(cast(escolari as int)) 'Total Sum Years of Schooling', "
"sum(case when escolari < 5 then 1 else 0 end) as 'JM_People_Educ_LT5', "
"sum(case when escolari < 10 then 1 else 0 end) as 'JM_People_Educ_LT10', "
"sum(case when escolari < 15 then 1 else 0 end) as 'JM_People_Educ_LT15', "
"sum(case when escolari < 20 then 1 else 0 end) as 'JM_People_Educ_LT20', "
"sum(case when escolari < 25 then 1 else 0 end) as 'JM_People_Educ_LT25', "
"sum(case when rez_esc = 1 then 1 else 0 end) as 'JM_1YrBehindSchool', "
"sum(case when rez_esc = 2 then 1 else 0 end) as 'JM_2YrBehindSchool', "
"sum(case when rez_esc = 3 then 1 else 0 end) as 'JM_3YrBehindSchool', "
"sum(case when rez_esc = 4 then 1 else 0 end) as 'JM_4YrBehindSchool', "
```

```
"sum(case when rez_esc = 5 then 1 else 0 end) as 'JM_5YrBehindSchool', "
"sum(cast(dis as int)) as 'JM_Sum_of_Disabled', "
"sum(cast(male as int)) as 'JM_Sum_Of_Males', "
"sum(cast(female as int)) as 'JM_Sum_Of_Females', "
"sum(cast(estadocivil1 as int)) as  'JM_estadocivil1', "
"sum(cast(estadocivil2 as int)) as  'JM_estadocivil2', "
"sum(cast(estadocivil3 as int)) as  'JM_estadocivil3', "
"sum(cast(estadocivil4 as int)) as  'JM_estadocivil4', "
"sum(cast(estadocivil5 as int)) as  'JM_estadocivil5', "
"sum(cast(estadocivil6 as int)) as  'JM_estadocivil6', "
"sum(cast(estadocivil7 as int)) as  'JM_estadocivil7', "
"sum(cast(parentesco1 as int)) as  'JM_parentesco1', "
"sum(cast(parentesco2 as int)) as  'JM_parentesco2', "
"sum(cast(parentesco3 as int)) as  'JM_parentesco3', "
"sum(cast(parentesco4 as int)) as  'JM_parentesco4', "
"sum(cast(parentesco5 as int)) as  'JM_parentesco5', "
"sum(cast(parentesco6 as int)) as  'JM_parentesco6', "
"sum(cast(parentesco7 as int)) as  'JM_parentesco7', "
"sum(cast(parentesco8 as int)) as  'JM_parentesco8', "
"sum(cast(parentesco9 as int)) as  'JM_parentesco9', "
"sum(cast(parentesco10 as int)) as  'JM_parentesco10', "
"sum(cast(parentesco11 as int)) as  'JM_parentesco11', "
"sum(cast(parentesco12 as int)) as  'JM_parentesco12', "
"sum(cast(instlevel1 as int)) as  'JM_instlevel1', "
"sum(cast(instlevel2 as int)) as  'JM_instlevel2', "
"sum(cast(instlevel3 as int)) as  'JM_instlevel3', "
"sum(cast(instlevel4 as int)) as  'JM_instlevel4', "
"sum(cast(instlevel5 as int)) as  'JM_instlevel5', "
"sum(cast(instlevel6 as int)) as  'JM_instlevel6', "
"sum(cast(instlevel7 as int)) as  'JM_instlevel7', "
"sum(cast(instlevel8 as int)) as  'JM_instlevel8', "
"sum(cast(instlevel9 as int)) as  'JM_instlevel9', "
"sum(cast(mobilephone as int)) as  'JM_mobilephone'"
"from train "
"group by idhogar "
))



test_member_agg = pd.DataFrame(sqldf("select  "
"idhogar, "
"sum(cast(v18q as int)) 'JM_Sum_of_Tablets', "
"sum(cast(escolari as int)) 'Total Sum Years of Schooling', "
"sum(case when escolari < 5 then 1 else 0 end) as 'JM_People_Educ_LT5', "
"sum(case when escolari < 10 then 1 else 0 end) as 'JM_People_Educ_LT10', "
"sum(case when escolari < 15 then 1 else 0 end) as 'JM_People_Educ_LT15', "
"sum(case when escolari < 20 then 1 else 0 end) as 'JM_People_Educ_LT20', "
"sum(case when escolari < 25 then 1 else 0 end) as 'JM_People_Educ_LT25', "
```

```
"sum(case when rez_esc = 1 then 1 else 0 end) as 'JM_1YrBehindSchool', "
"sum(case when rez_esc = 2 then 1 else 0 end) as 'JM_2YrBehindSchool', "
"sum(case when rez_esc = 3 then 1 else 0 end) as 'JM_3YrBehindSchool', "
"sum(case when rez_esc = 4 then 1 else 0 end) as 'JM_4YrBehindSchool', "
"sum(case when rez_esc = 5 then 1 else 0 end) as 'JM_5YrBehindSchool', "
"sum(cast(dis as int)) as 'JM_Sum_of_Disabled', "
"sum(cast(male as int)) as 'JM_Sum_Of_Males', "
"sum(cast(female as int)) as 'JM_Sum_Of_Females', "
"sum(cast(estadocivil1 as int)) as  'JM_estadocivil1', "
"sum(cast(estadocivil2 as int)) as  'JM_estadocivil2', "
"sum(cast(estadocivil3 as int)) as  'JM_estadocivil3', "
"sum(cast(estadocivil4 as int)) as  'JM_estadocivil4', "
"sum(cast(estadocivil5 as int)) as  'JM_estadocivil5', "
"sum(cast(estadocivil6 as int)) as  'JM_estadocivil6', "
"sum(cast(estadocivil7 as int)) as  'JM_estadocivil7', "
"sum(cast(parentesco1 as int)) as  'JM_parentesco1', "
"sum(cast(parentesco2 as int)) as  'JM_parentesco2', "
"sum(cast(parentesco3 as int)) as  'JM_parentesco3', "
"sum(cast(parentesco4 as int)) as  'JM_parentesco4', "
"sum(cast(parentesco5 as int)) as  'JM_parentesco5', "
"sum(cast(parentesco6 as int)) as  'JM_parentesco6', "
"sum(cast(parentesco7 as int)) as  'JM_parentesco7', "
"sum(cast(parentesco8 as int)) as  'JM_parentesco8', "
"sum(cast(parentesco9 as int)) as  'JM_parentesco9', "
"sum(cast(parentesco10 as int)) as  'JM_parentesco10', "
"sum(cast(parentesco11 as int)) as  'JM_parentesco11', "
"sum(cast(parentesco12 as int)) as  'JM_parentesco12', "
"sum(cast(instlevel1 as int)) as  'JM_instlevel1', "
"sum(cast(instlevel2 as int)) as  'JM_instlevel2', "
"sum(cast(instlevel3 as int)) as  'JM_instlevel3', "
"sum(cast(instlevel4 as int)) as  'JM_instlevel4', "
"sum(cast(instlevel5 as int)) as  'JM_instlevel5', "
"sum(cast(instlevel6 as int)) as  'JM_instlevel6', "
"sum(cast(instlevel7 as int)) as  'JM_instlevel7', "
"sum(cast(instlevel8 as int)) as  'JM_instlevel8', "
"sum(cast(instlevel9 as int)) as  'JM_instlevel9', "
"sum(cast(mobilephone as int)) as  'JM_mobilephone'"
"from test "
"group by idhogar "
))



#Join the household and member aggregation together
train_model_set = pd.DataFrame(pd.merge(train_head, train_member_agg, on = 'idhogar',
test_model_set = pd.DataFrame(pd.merge(test_head, test_member_agg, on = 'idhogar', how
```

```
# For the rest of the v2a1 that are null, we will use the mean

train_model_set['v2a1'].fillna((train_model_set['v2a1'].mean()), inplace=True)

test_model_set['v2a1'].fillna((train_model_set['v2a1'].mean()), inplace=True)

#Export final model csvs for review
train_model_set.to_csv("train_model_set.csv")
test_model_set.to_csv("test_model_set.csv")

#Make sure all Nulls are accounted for
null_columns=train_model_set.columns[train_model_set.isnull().any()]

train_model_set[null_columns].isnull().sum()
```

Out[12]: Series([], dtype: float64)

4 Simple Statistics

Requirement: Visualize appropriate statistics (e.g. range, mode, mean, median, variance, counts) for a subset of attributes. Describe anything meaningful you found from this or if you found something potentially niteresting. Note: You can also use data from other sources for comparison. Explain why the statistics run are meaningful.

In [5]:
```
pd.options.display.float_format = '{:.2f}'.format

train_model_set.describe()
```

Out[5]:

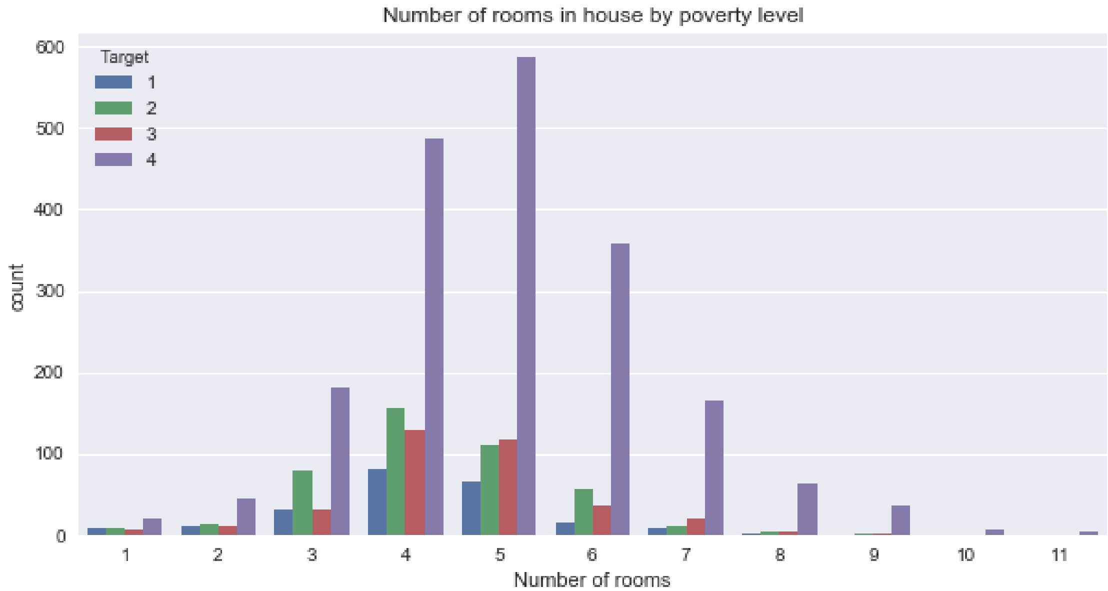
	parentesco1	hhsize	v2a1	hacdor	rooms	hacapo	v14a	refrig	\
count	2973.00	2973.00	2673.00	2973.00	2973.00	2973.00	2973.00	2973.00	
mean	1.00	3.21	51596.37	0.02	4.79	0.01	0.99	0.95	
std	0.00	1.59	117781.50	0.14	1.45	0.11	0.08	0.21	
min	1.00	1.00	0.00	0.00	1.00	0.00	0.00	0.00	
25%	1.00	2.00	0.00	0.00	4.00	0.00	1.00	1.00	
50%	1.00	3.00	0.00	0.00	5.00	0.00	1.00	1.00	
75%	1.00	4.00	60000.00	0.00	6.00	0.00	1.00	1.00	
max	1.00	13.00	2353477.00	1.00	11.00	1.00	1.00	1.00	

	v18q1	r4h1	...	JM_instlevel1	JM_instlevel2	\
count	2973.00	2973.00	...	2973.00	2973.00	
mean	0.10	0.26	...	0.43	0.54	
std	0.40	0.56	...	0.72	0.78	
min	0.00	0.00	...	0.00	0.00	
25%	0.00	0.00	...	0.00	0.00	
50%	0.00	0.00	...	0.00	0.00	
75%	0.00	0.00	...	1.00	1.00	

```
max       4.00     5.00        ...                  5.00            5.00

       JM_instlevel3  JM_instlevel4  JM_instlevel5  JM_instlevel6  \
count        2973.00        2973.00        2973.00        2973.00
mean            0.67           0.60           0.36           0.06
std             0.84           0.83           0.63           0.26
min             0.00           0.00           0.00           0.00
25%             0.00           0.00           0.00           0.00
50%             0.00           0.00           0.00           0.00
75%             1.00           1.00           1.00           0.00
max             7.00           5.00           4.00           3.00

       JM_instlevel7  JM_instlevel8  JM_instlevel9  JM_mobilephone
count        2973.00        2973.00        2973.00         2973.00
mean            0.05           0.45           0.05            3.13
std             0.24           0.75           0.24            1.67
min             0.00           0.00           0.00            0.00
25%             0.00           0.00           0.00            2.00
50%             0.00           0.00           0.00            3.00
75%             0.00           1.00           0.00            4.00
max             3.00           5.00           2.00           13.00

[8 rows x 145 columns]
```

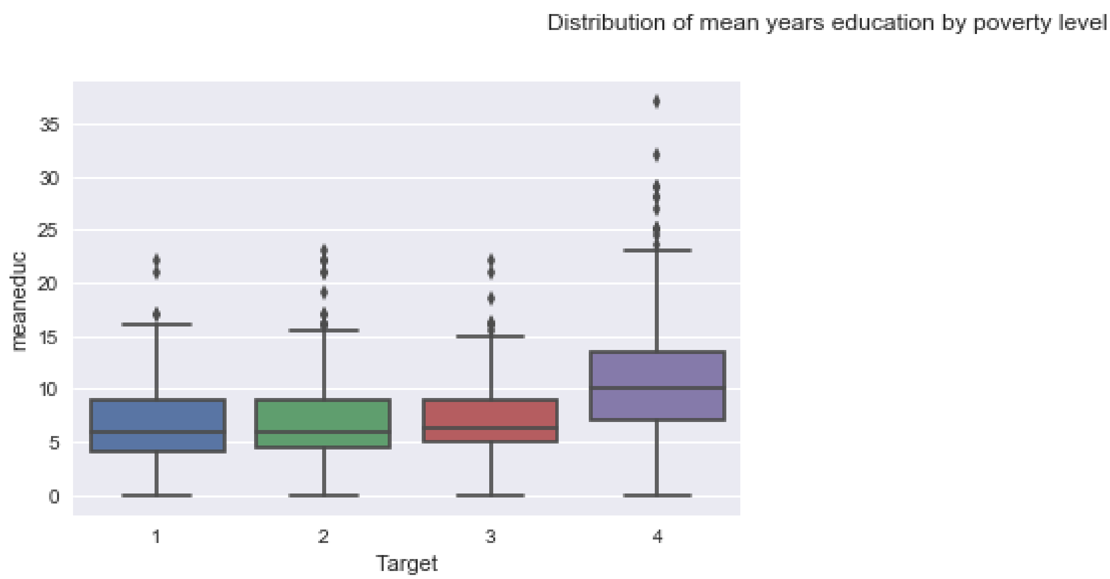
5 Visualize Attributes

In [68]:
```python
# Number of rooms by poverty level
train_by_hhid = train_model_set.groupby('idhogar')
rm_by_id = train_by_hhid['Target', 'rooms'].first()
plt.figure(figsize=(10, 5));
sns.countplot(x='rooms', hue='Target', data=rm_by_id);
plt.title('Number of rooms in house by poverty level');
plt.xlabel('Number of rooms');
```



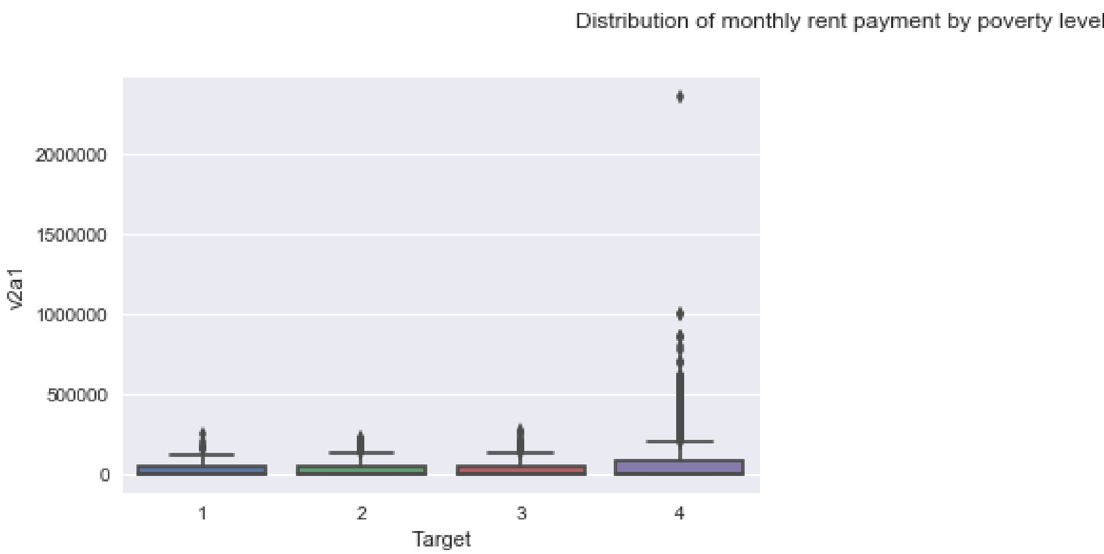
The first variable that we looked at is the total number of rooms in the individual's house. We have aggregated by household to ensure that there is no double counting of homes. The most common number of rooms for people that are not vulnerable is 5 rooms while the number of rooms for the most vulnerable (extreme, moderate, and vulnerable to poverty) households is 4 rooms. Very few households experiencing poverty or vulnerable have more than 5 rooms.

In [69]:
```
# Box plot of Education by poverty level
fig, (ax1) = plt.subplots(1); sns.boxplot(x='Target', y='meaneduc', data=train_model_s
fig.suptitle('Distribution of mean years education by poverty level', x=1, y=1, multia
```



There is very little distinction in mean years of education in the target groups that are extreme, moderate, or are vulnerable with the mean of each roughly around 5. Meanwhile, those who are not vulnerable have a mean of roughly 10.

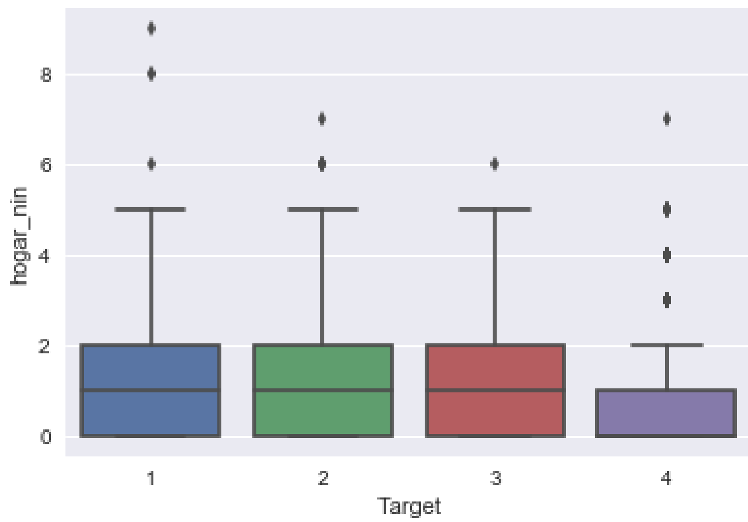
```
In [70]: # Box plot of monthly rent payment by poverty level
         fig, (ax1) = plt.subplots(1); sns.boxplot(x='Target', y='v2a1', data=train_model_set,
         fig.suptitle('Distribution of monthly rent payment by poverty level', x=1, y=1);
```



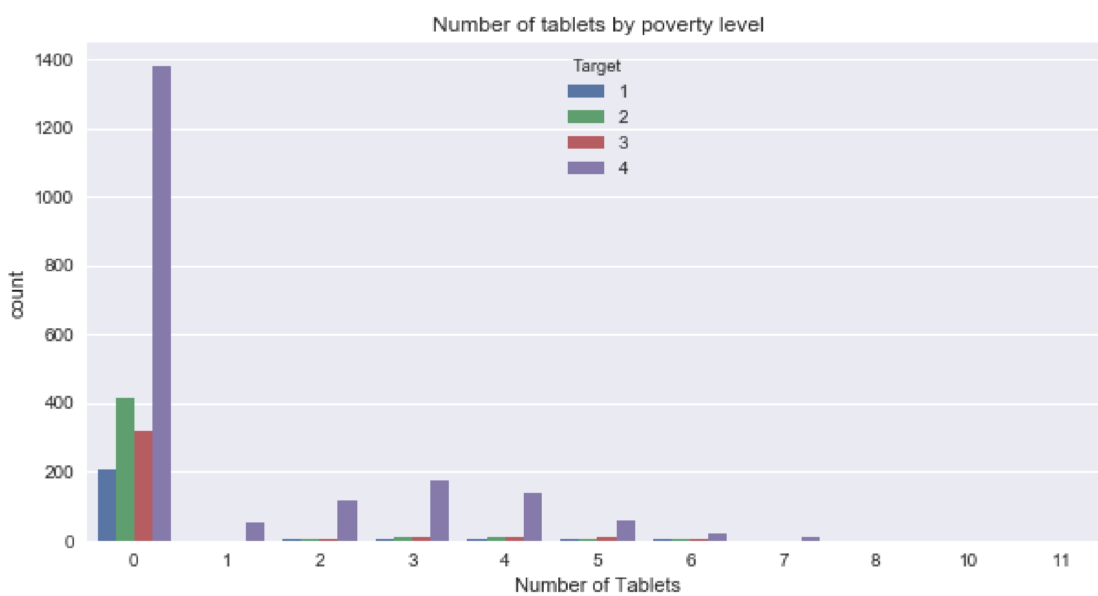
Similar to mean years of education, there is not a significant difference in mean monthly rent for the target groups that are extreme, moderate, or are vulnerable, but there is a wider range of rent in the moderate and vulnerable groups. Also, the non-vulnerable group appears to have a higher rent than the other groups.

```
In [73]: # Box Plot of Total Number of adults per household
         fig, (ax1) = plt.subplots(1); sns.boxplot(x='Target', y='hogar_nin', data=train_model_
         fig.suptitle('Number of adults per household by poverty level', x=1, y=1);
```

Number of adults per household by poverty level

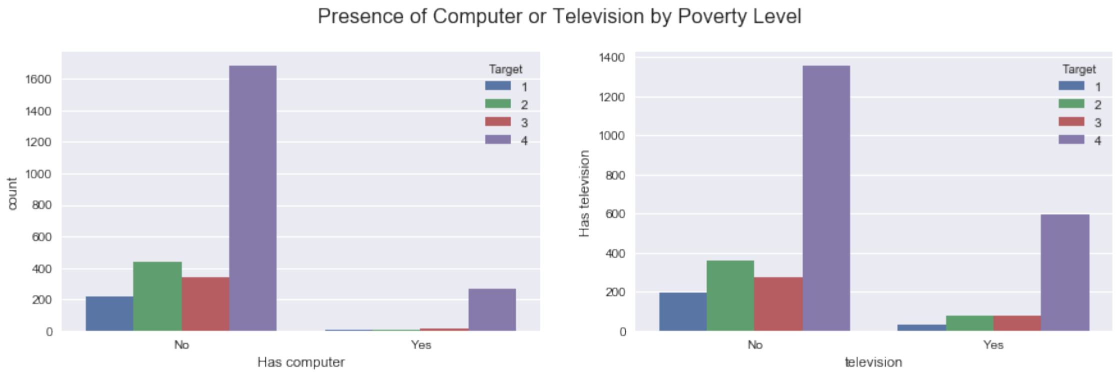


In [88]:
```
# Numbers of Tablets by poverty level
tablets_by_id = train_by_hhid['Target', 'JM_Sum_of_Tablets'].first()
plt.figure(figsize=(10, 5));
sns.countplot(x='JM_Sum_of_Tablets', hue='Target', data= tablets_by_id);
plt.title('Number of tablets by poverty level');
plt.xlabel('Number of Tablets');
```



In reviewing the number of tablets by poverty level per household, the majority of households with extreme, moderate, and vulnerable to poverty groups have zero tablets. While the majority of households that are not vulnerable to poverty also have no tablets, households that have one or more tablet are almost exclusively not vulnerable to poverty.

```
In [67]: # Presence of computer or television by poverty level
         comp_tv_by_id = train_by_hhid['Target', 'computer', 'television'].first()
         fig, (ax1, ax2) = plt.subplots(1, 2)
         sns.countplot(x='computer', hue='Target', data=comp_tv_by_id, ax=ax1);
         sns.countplot(x='television', hue='Target', data=comp_tv_by_id, ax=ax2);
         ax1.set_xticklabels(['No', 'Yes']);
         ax2.set_xticklabels(['No', 'Yes']);
         ax1.set_xlabel('Has computer');
         ax2.set_ylabel('Has television');
         fig.subplots_adjust(left=0.1, right=2)
         fig.suptitle('Presence of Computer or Television by Poverty Level', x=1, y=1, fontsiz
```



There does not appear to be a significant distinction in the households that do not have a computer relative to the level of poverty. On the other hand, few households that are in the target groups 1 through 3 while there is a significantly higher number of households that have a computer that are not vulnerable.

There is a similar distribution of households with a television relative to those that have a computer. There does not appear to be a significant distinction in the households that do not have a television relative to the level of poverty. On the other hand, few households that are in the target groups 1 through 3 while there is a significantly higher number of households that have a television that are not vulnerable.

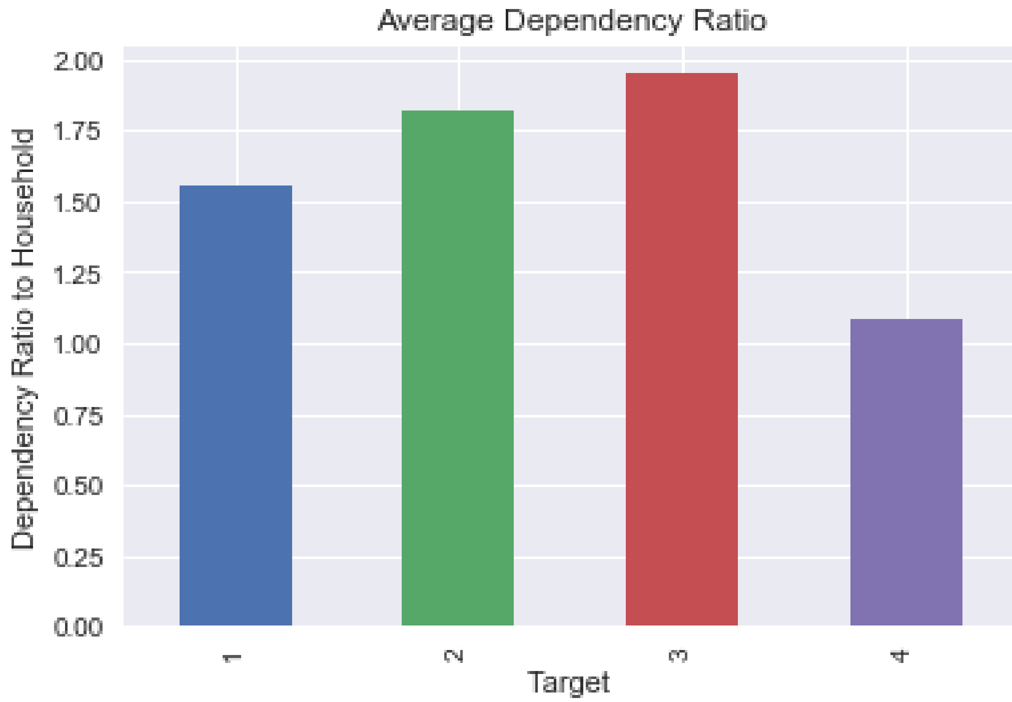
6 Explore Joint Attributes

Identify and explain interesting relationships between features and the class you are trying to predict (i.e., relationships with variables and the target classsification).

```
In [89]: train_intvars = train_model_set[['Target','dependency','r4m3','hogar_nin','tipovivi3'
         train_intvars['dependency'] = train_intvars['dependency'].astype(np.float64)
```

```python
print(train_intvars.describe())

dependency_group = train_intvars.groupby(by=['Target'])
average_dependency=dependency_group.dependency.mean()
ax = average_dependency.plot(kind='bar')
plt.ylabel('Dependency Ratio to Household')
plt.title('Average Dependency Ratio')
print(average_dependency)
```

```
C:\Anaconda\lib\site-packages\ipykernel_launcher.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html



            Target   dependency         r4m3    hogar_nin    tipovivi3  \
count  2973.000000  2973.000000  2973.000000  2973.000000  2973.000000
mean      3.359233     1.334008     1.665994     0.967037     0.180626
std       0.987870     2.145635     1.071679     1.158497     0.384772
min       1.000000     0.000000     0.000000     0.000000     0.000000
25%       3.000000     0.000000     1.000000     0.000000     0.000000
50%       4.000000     0.500000     1.000000     1.000000     0.000000
75%       4.000000     1.000000     2.000000     2.000000     0.000000
max       4.000000     8.000000     8.000000     9.000000     1.000000

              r4t3         r4h3
count  2973.000000  2973.000000
mean      3.221662     1.555668
std       1.587820     1.058840
min       1.000000     0.000000
25%       2.000000     1.000000
50%       3.000000     1.000000
75%       4.000000     2.000000
max      13.000000     8.000000
Target
1    1.556306
2    1.819834
3    1.951315
4    1.086705
Name: dependency, dtype: float64
```

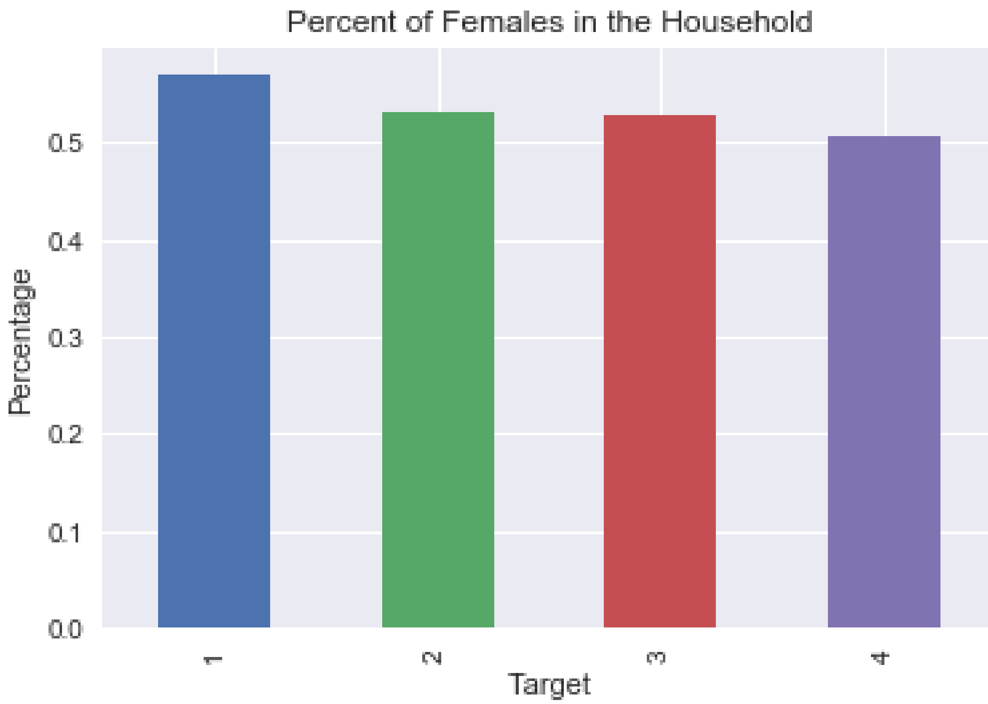


When looking at the average dependency ratio for each poverty level, we see that poverty levels 1 to 3 are higher than 4. The trend seems to indiciate that people of less poverty have lower number of depencies compared to higher poverty levels. This could indicate that the management of money is spread out more thinly because of higher number of dependents.

```
In [90]: females_hh = train_intvars.groupby(by=['Target'])
         female_total = females_hh.r4m3.sum()
         female_pct=females_hh.r4m3.sum() / females_hh.r4t3.sum()
         fx = female_pct.plot(kind='bar')
         plt.ylabel('Percentage')
         plt.title('Percent of Females in the Household')

         print(female_total)
         print(female_pct)
```

```
Target
1     441
2     831
3     636
4    3045
Name: r4m3, dtype: int64
Target
1    0.569032
2    0.531670
3    0.527363
```

```
4    0.504640
dtype: float64
```

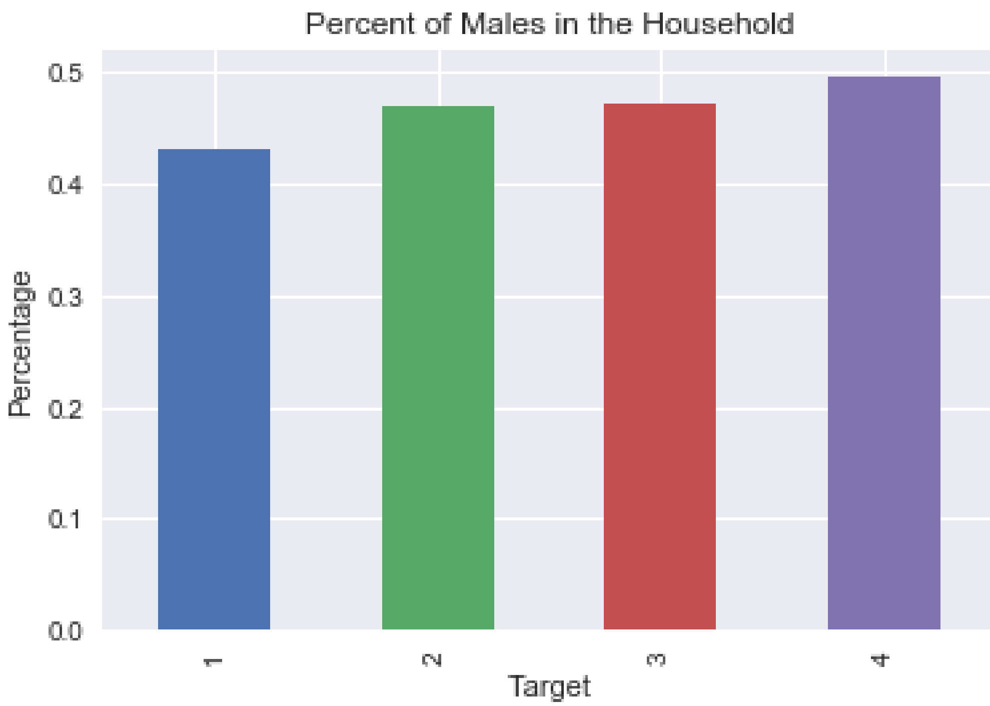


When looking at the number of females in a given household as a percentage, we see that the trend is going downwards as the poverty level decreases. This could indicate that females may have obstacles in terms of obtaining meaningful income if there is such as high number of females percentage wise in the lower income levels.

```
In [91]: males_hh = train_intvars.groupby(by=['Target'])
         male_total = males_hh.r4h3.sum()
         male_pct=males_hh.r4h3.sum() / males_hh.r4t3.sum()
         mx = male_pct.plot(kind='bar')
         plt.ylabel('Percentage')
         plt.title('Percent of Males in the Household')
         print(male_total)
         print(male_pct)
```

```
Target
1     334
2     732
3     570
4    2989
Name: r4h3, dtype: int64
Target
```

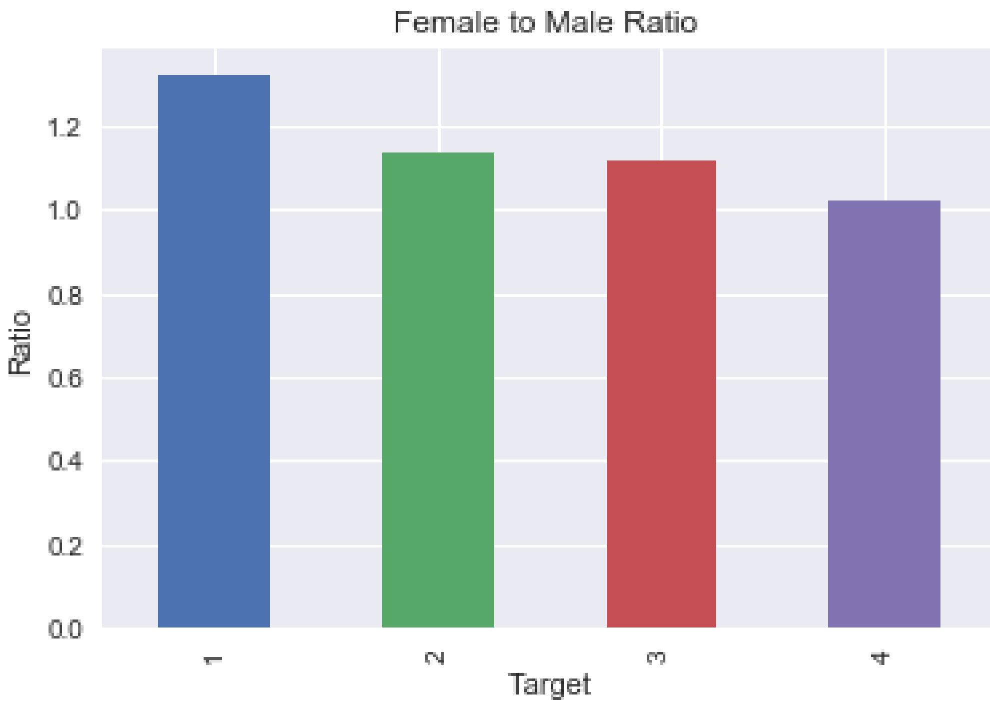
```
1    0.430968
2    0.468330
3    0.472637
4    0.495360
dtype: float64
```



Looking at the number of males based on percentage of household, we can see an upward trend as poverty level increases. This seems to show that males have less obstacles in obtaining meaningful income. When looking at the graph for male and female percentages, we see that the story shows there could be disparity between males and females.

```
In [92]: fm_ratio = train_intvars.groupby(by=['Target'])
         fm_ratio_comp=fm_ratio.r4m3.sum() / fm_ratio.r4h3.sum()
         fmx = fm_ratio_comp.plot(kind='bar')
         plt.ylabel('Ratio')
         plt.title('Female to Male Ratio ')
         print(fm_ratio_comp)
```

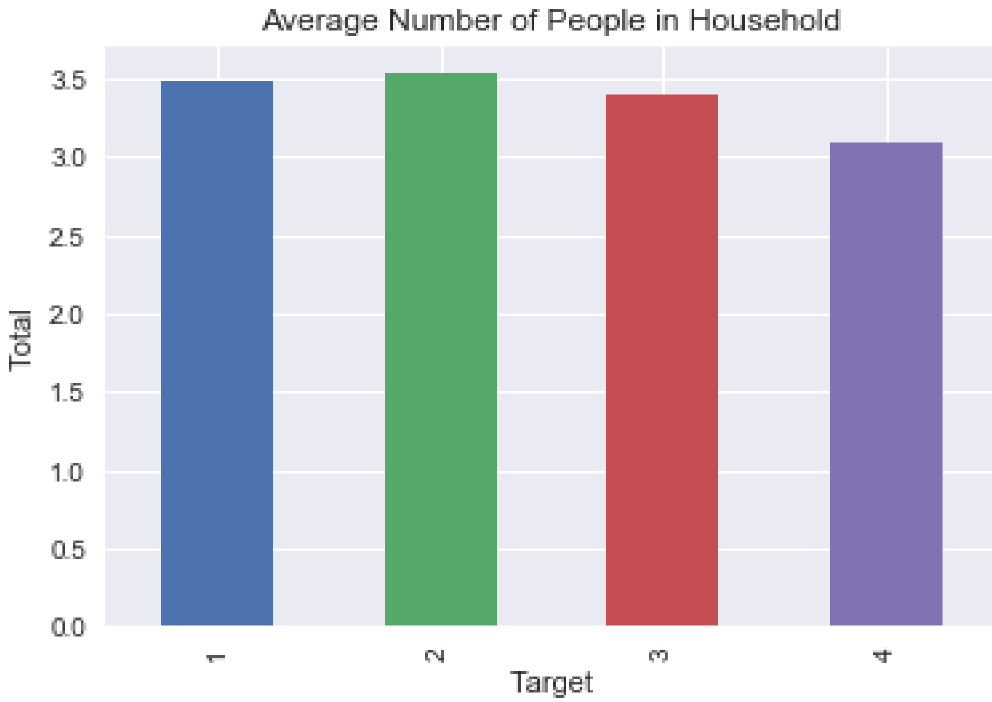
```
Target
1    1.320359
2    1.135246
3    1.115789
4    1.018735
dtype: float64
```



When looking at the female to male ratio, this further shows the disparity in poverty between females and males. Seeing that females are of higher ratio in the poverty level 1, shows that there could issues in income disparity or adverse selection against females in the workforce.

```
In [93]: household_ppl = train_intvars.groupby(by=['Target'])
         household_cnt=household_ppl.r4t3.mean()
         hx = household_cnt.plot(kind='bar')
         plt.ylabel('Total')
         plt.title('Average Number of People in Household')

         print(household_cnt)
```

```
Target
1    3.490991
2    3.536199
3    3.397183
4    3.088025
Name: r4t3, dtype: float64
```

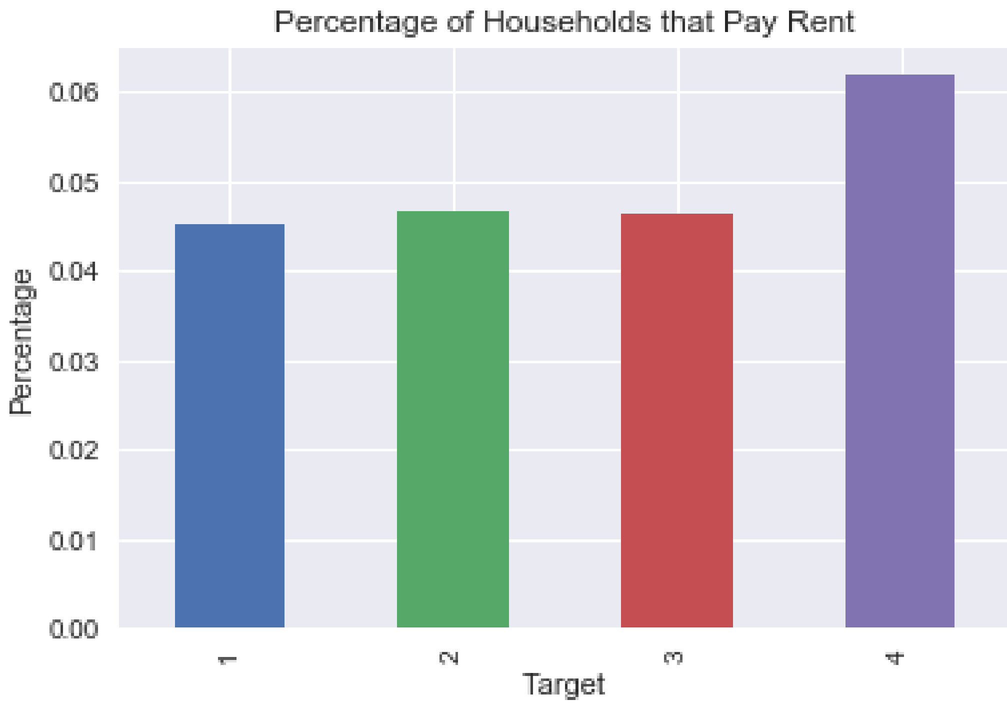


The average of number of households decreases as poverty level decreases going for 3.49 to 3.09. This seems to go hand in hand with the dependency relationship stated earlier, indicating that larger households could indicate more dependents meaning less individuals who can share the cost of the household.

```
In [94]: rent = train_intvars.groupby(by=['Target'])
         rent_cnt=rent.tipovivi3.sum()/rent.r4t3.sum()
         rent_count = rent.tipovivi3.sum()
         rx = rent_cnt.plot(kind='bar')
         plt.ylabel('Percentage')
         plt.title('Percentage of Households that Pay Rent')

         print(rent_count)
         print(rent_cnt)
```

```
Target
1     35
2     73
3     56
4    373
Name: tipovivi3, dtype: int64
Target
1    0.045161
2    0.046705
3    0.046434
```

```
4    0.061816
dtype: float64
```

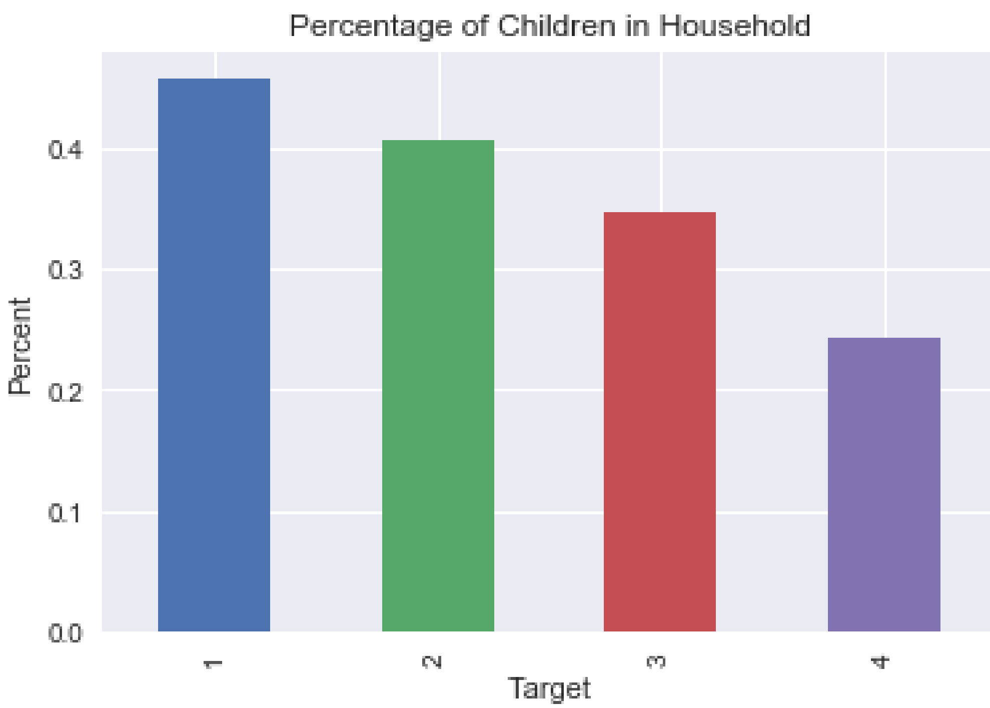


When looking at the percentage of households that pay rent, we see that the lower poverty levels have more households that pay rent. This seems to show that people of higher poverty levels are not able to afford the rent or already own a house. This could also be an indicator that these households may not have a shelter to live since rent cannot be afforded.

```
In [95]: child = train_intvars.groupby(by=['Target'])
         child_pct=child.hogar_nin.sum()/child.r4t3.sum()
         child_cnt = child.hogar_nin.sum()
         ppl = child.r4t3.sum()
         cctx = child_pct.plot(kind='bar')
         plt.ylabel('Percent')
         plt.title('Percentage of Children in Household')

         print(ppl)
         print(child_cnt)
         print(child_pct)
```

```
Target
1      775
2     1563
3     1206
```

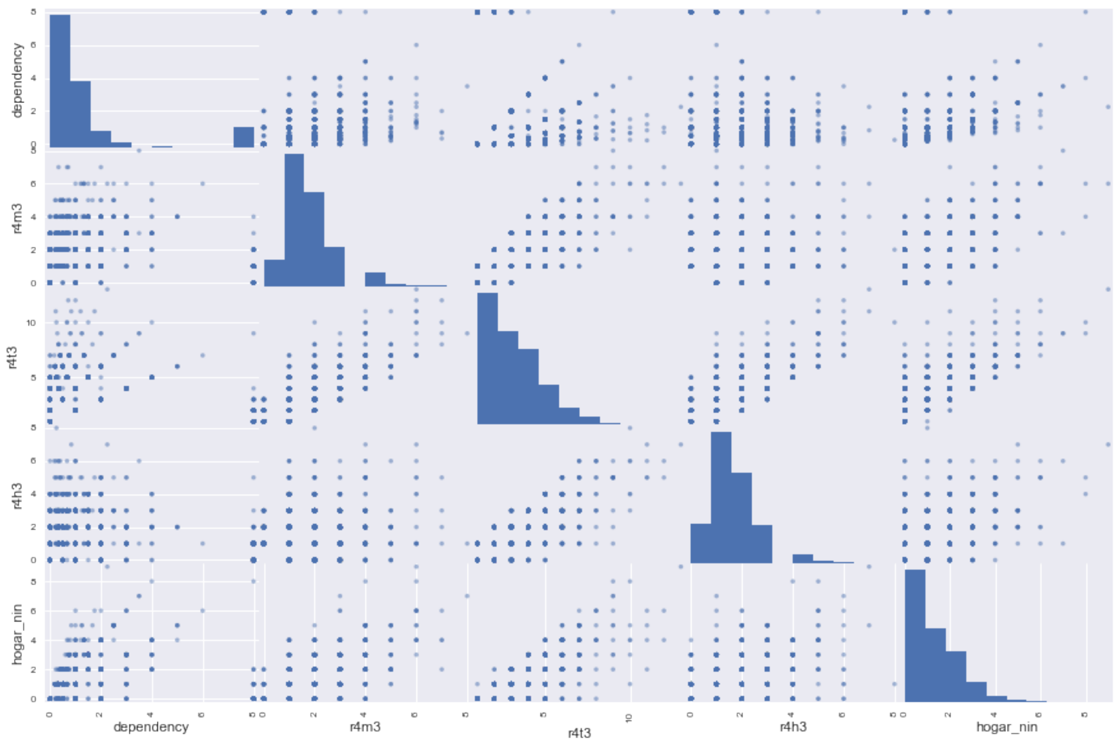
```
4    6034
Name: r4t3, dtype: int64
Target
1     354
2     634
3     418
4    1469
Name: hogar_nin, dtype: int64
Target
1    0.456774
2    0.405630
3    0.346600
4    0.243454
dtype: float64
```



The percentage of children in the household is a further breakdown of dependencies, since dependencies can include old and young. The trend seems to be a downward trend as poverty level decreases. This also shows that a large percentage of individuals for dependencies are children. This could help determine where the large cost of household is concentrated on.

```
In [96]: from pandas.tools.plotting import scatter_matrix
         btw_intvars = train_model_set[['dependency','r4m3','r4t3','r4h3','hogar_nin']]
         btw_intvars['dependency'] = btw_intvars['dependency'].astype(np.float64)
         sx = scatter_matrix(btw_intvars,figsize=(15, 10))
```

```
C:\Anaconda\lib\site-packages\ipykernel_launcher.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
  This is separate from the ipykernel package so we can avoid doing imports until
C:\Anaconda\lib\site-packages\ipykernel_launcher.py:4: FutureWarning: 'pandas.tools.plotting.sc
  after removing the cwd from sys.path.
```



The scatterplot and histrogram matrix is to see if there is any interesting correlations between the explanatory variables given earlier in the analysis. When looking at the scatterplots, we can see that there is some type of relationship between number of children (hogar_nin) and total number of females (r4m3) and total number of household (r4t3). They all show a positive relationship between the three variables. The number of children (hogar_nin) and dependency also show a positive relationship between the two variables. The total number of household all show a positive relationship between the total number of females, total number of males, total of number of children, and dependency. These correlations are to be kept in mind when looking at regression modeling since there could be residual issues when using highly correlated variables. When looking at the histograms, we can see that they are left skewed. This seems to show that the variables have higher counts near the lower end of the scale indicating lower number of dependicies, children, etc..

7 New Features

New Field Name	Definition	Variable Type
JM_1YrBehindSchool	Count of individuals when rez_esc Count of 1	int
JM_2YrBehindSchool	Count of individuals when rez_esc Count of 2	int
JM_3YrBehindSchool	Count of individuals when rez_esc Count of 3	int
JM_4YrBehindSchool	Count of individuals when rez_esc Count of 4	int
JM_5YrBehindSchool	Count of individuals when rez_esc Count of 5	int
JM_estadocivil1	Count of children 1 if less than 10 years old	int
JM_estadocivil2	Count of people if free or coupled uunion	int
JM_estadocivil3	Count of people if married	int
JM_estadocivil4	Count of people if divorced	int
JM_estadocivil5	Count of people if separated	int

New Field Name	Definition	Variable Type
JM_estadocivil6	Count of people if widow/er	int
JM_estadocivil7	Count of people if single	int
JM_instlevel1	Count of people no level of education	int
JM_instlevel2	Count of people incomplete primary	int
JM_instlevel3	Count of people complete primary	int
JM_instlevel4	Count of people incomplete academic secondary level	int
JM_instlevel5	Count of people complete academic secondary level	int
JM_instlevel6	Count of people incomplete technical secondary level	int
JM_instlevel7	Count of people complete technical secondary level	int

New Field Name	Definition	Variable Type
JM_instlevel8	Count of people undergraduate and higher education	int
JM_instlevel9	Count of people postgraduate higher education	int
JM_mobilephone	Count of people if mobile phone	int
JM_parentesco1	Count of people if household head	int
JM_parentesco10	Count of people if brother/sister in law	int
JM_parentesco11	Count of people if other family member	int
JM_parentesco12	Count of people if other non family member	int
JM_parentesco2	Count of people if spouse/partner	int
JM_parentesco3	Count of people if son/doughter	int
JM_parentesco4	Count of people if stepson/doughter	int
JM_parentesco5	Count of people if son/doughter in law	int

New Field Name	Definition	Variable Type
JM_parentesco6	Count of people if grandson/doughter	int
JM_parentesco7	Count of people if mother/father	int
JM_parentesco8	Count of people if father/mother in law	int
JM_parentesco9	Count of people if brother/sister	int
JM_People_Educ_LT10	Count of individuals when schooling (escolari) < 10	int
JM_People_Educ_LT15	Count of individuals when schooling (escolari) < 15	int
JM_People_Educ_LT20	Count of individuals when schooling (escolari) < 20	int
JM_People_Educ_LT25	Count of individuals when schooling (escolari) < 25	int
JM_People_Educ_LT5	Count of individuals when schooling (escolari) < 5	int

New Field Name	Definition	Variable Type
JM_Sum_of_Disabled	Sum of dis for total number of disabled individuals per household	int
JM_Sum_Of_Females	Sum of male for total number of females per household	int
JM_Sum_Of_Males	Sum of male for total number of males per household	int
JM_Sum_of_Tablets	Sum of v18q for total tablets per household	int
Total Sum Years of Schooling	Sum of escolari for total years of schooling per household	int

8 Exceptional Work

Exceptional work here I believe should go to the amount of data cleaning that needed to occur to get the dataset ready. Denormalizaition was needed as the data was submitted at the member level, but the submission and model needs to occur at the household level. This added a lot more complexity and intimacy with the data to do this correctly and we added 28 new features from this.