

# Income Qualification Screenshots

Here are some screenshots from my source code. Much of this can be found in the PDF file of the source code, but the outputs are still listed here.

Columns pertaining to home ownership status

+ Code

+ Markdown

```
# Columns pertaining to home ownership status. Columns 2, 116-120

#trainDF.loc[:, ["v2a1", "tipovivi1", "tipovivi2", "tipovivi3", "tipovivi4", "tipovivi5", "Target"]].iloc[0: 60]
#trainDF.loc[:, ["v2a1", "tipovivi1", "tipovivi2", "tipovivi3", "tipovivi4", "tipovivi5", "Target"]].iloc[60: 120]
#trainDF.loc[:, ["v2a1", "tipovivi1", "tipovivi2", "tipovivi3", "tipovivi4", "tipovivi5", "Target"]].iloc[1050: 1100]
trainDF.loc[:, ["Id", "idhogar", "v2a1", "tipovivi1", "tipovivi2", "tipovivi3", "tipovivi4", "tipovivi5", "Target"]].iloc[1086: 1100]
```

✓ 0.0s

	Id	idhogar	v2a1	tipovivi1	tipovivi2	tipovivi3	tipovivi4	tipovivi5	Target
1086	ID_30d6500c3	2e65e4af3	150000.0	0	0	1	0	0	4
1087	ID_4203fd5e2	ee3d80cb6	NaN	1	0	0	0	0	2
1088	ID_7c33c1884	a0695cb68	NaN	1	0	0	0	0	1
1089	ID_77cce5b75	62c28e034	NaN	1	0	0	0	0	4
1090	ID_df05b9e45	62c28e034	NaN	1	0	0	0	0	4
1091	ID_3490fd704	8e284abd5	NaN	1	0	0	0	0	4
1092	ID_d82b1a426	8e284abd5	NaN	1	0	0	0	0	4
1093	ID_9d6957e8a	8e284abd5	NaN	1	0	0	0	0	4
1094	ID_5038a636a	304731467	160000.0	0	0	1	0	0	2
1095	ID_6c29eea22	304731467	160000.0	0	0	1	0	0	2
1096	ID_870ae3993	304731467	160000.0	0	0	1	0	0	2
1097	ID_00da43675	304731467	160000.0	0	0	1	0	0	2
1098	ID_22d124fdf	304731467	160000.0	0	0	1	0	0	2
1099	ID_075c52143	304731467	160000.0	0	0	1	0	0	2

## Columns pertaining to number of rooms and overcrowding

```
# Columns pertaining to number of rooms and overcrowding. Columns 3-6, 114, 115

#trainDF.loc[:, ["hacdor", "rooms", "hacapo", "bedrooms", "overcrowding", "Target"]].iloc[0: 60]
#trainDF.loc[:, ["hacdor", "rooms", "hacapo", "bedrooms", "overcrowding", "Target"]].iloc[60: 120]
#trainDF.loc[:, ["hacdor", "rooms", "hacapo", "bedrooms", "overcrowding", "Target"]].iloc[1050: 1100]
trainDF.loc[:, ["Id", "idhogar", "hacdor", "rooms", "hacapo", "bedrooms", "overcrowding", "Target"]].iloc[1086: 1100]
```

	Id	idhogar	hacdor	rooms	hacapo	bedrooms	overcrowding	Target
1086	ID_30d6500c3	2e65e4af3	0	4	0	2	2.500000	4
1087	ID_4203fd5e2	ee3d80cb6	0	3	0	1	1.000000	2
1088	ID_7c33c1884	a0695cb68	0	6	0	3	0.333333	1
1089	ID_77cce5b75	62c28e034	0	4	0	2	1.000000	4
1090	ID_df05b9e45	62c28e034	0	4	0	2	1.000000	4
1091	ID_3490fd704	8e284abd5	0	7	0	4	2.500000	4
1092	ID_d82b1a426	8e284abd5	0	7	0	4	2.500000	4
1093	ID_9d6957e8a	8e284abd5	0	7	0	4	2.500000	4
1094	ID_5038a636a	304731467	0	5	0	3	2.000000	2
1095	ID_6c29eea22	304731467	0	5	0	3	2.000000	2
1096	ID_870ae3993	304731467	0	5	0	3	2.000000	2
1097	ID_00da43675	304731467	0	5	0	3	2.000000	2
1098	ID_22d124fdf	304731467	0	5	0	3	2.000000	2
1099	ID_075c52143	304731467	0	5	0	3	2.000000	2

## Columns pertaining to number and type of people in home

```
# Columns pertaining to number and type of people in home. Columns 10-20, 23

#trainDF.loc[:, ["r4h1", "r4h2", "r4h3", "r4m1", "r4m2", "r4m3", "r4t1", "r4t2", "r4t3", "tamhog", "tamviv", "hhsiz", "Target"]].iloc[0: 60]
#trainDF.loc[:, ["r4h1", "r4h2", "r4h3", "r4m1", "r4m2", "r4m3", "r4t1", "r4t2", "r4t3", "tamhog", "tamviv", "hhsiz", "Target"]].iloc[60: 120]
#trainDF.loc[:, ["r4h1", "r4h2", "r4h3", "r4m1", "r4m2", "r4m3", "r4t1", "r4t2", "r4t3", "tamhog", "tamviv", "hhsiz", "Target"]].iloc[1050: 1100]
trainDF.loc[:, ["Id", "idhogar", "r4h1", "r4h2", "r4h3", "r4m1", "r4m2", "r4m3", "r4t1", "r4t2", "r4t3", "tamhog", "tamviv", "hhsiz", "Target"]].iloc[1086: 1100]
```

	Id	idhogar	r4h1	r4h2	r4h3	r4m1	r4m2	r4m3	r4t1	r4t2	r4t3	tamhog	tamviv	hhsiz	Target
1086	ID_30d6500c3	2e65e4af3	1	2	3	0	2	2	1	4	5	5	5	5	4
1087	ID_4203fd5e2	ee3d80cb6	0	1	1	0	0	0	0	1	1	1	1	1	2
1088	ID_7c33c1884	a0695cb68	0	0	0	0	1	1	0	1	1	1	1	1	1
1089	ID_77cce5b75	62c28e034	0	1	1	0	1	1	0	2	2	2	2	2	4
1090	ID_df05b9e45	62c28e034	0	1	1	0	1	1	0	2	2	2	2	2	4
1091	ID_3490fd704	8e284abd5	0	1	1	0	2	2	0	3	3	3	10	3	4
1092	ID_d82b1a426	8e284abd5	0	1	1	0	2	2	0	3	3	3	10	3	4
1093	ID_9d6957e8a	8e284abd5	0	1	1	0	2	2	0	3	3	3	10	3	4
1094	ID_5038a636a	304731467	0	3	3	1	2	3	1	5	6	6	6	6	2
1095	ID_6c29eea22	304731467	0	3	3	1	2	3	1	5	6	6	6	6	2
1096	ID_870ae3993	304731467	0	3	3	1	2	3	1	5	6	6	6	6	2
1097	ID_00da43675	304731467	0	3	3	1	2	3	1	5	6	6	6	6	2
1098	ID_22d124fdf	304731467	0	3	3	1	2	3	1	5	6	6	6	6	2
1099	ID_075c52143	304731467	0	3	3	1	2	3	1	5	6	6	6	6	2

Columns pertaining to house material quality

```
quality. Columns 24-31, 32-35, 37, 36

lzocalo", "paredpreb", "pareddes", "paredmad", "paredzinc", "paredfibras", "paredother", "pisomoscer", "pisocemento", "pisooother", "pisonatur", "pisomadera", "pisonotiene", "Target"]].iloc[0: 60]
lzocalo", "paredpreb", "pareddes", "paredmad", "paredzinc", "paredfibras", "paredother", "pisomoscer", "pisocemento", "pisooother", "pisonatur", "pisomadera", "pisonotiene", "Target"]].iloc[1050: 1100]
dblolad", "paredzocalo", "paredpreb", "pareddes", "paredmad", "paredzinc", "paredfibras", "paredother", "pisomoscer", "pisocemento", "pisooother", "pisonatur", "pisomadera", "pisonotiene", "Target"]].iloc[1086: 1100]
```

	Id	idhogar	paredblolad	paredzocalo	paredpreb	pareddes	paredmad	paredzinc	paredfibras	paredother	pisomoscer	pisocemento	pisooother	pisonatur	pisomadera	pisonotiene	Target
1086	ID_30d6500c3	2e65e4af3	1	0	0	0	0	0	0	0	1	0	0	0	0	0	4
1087	ID_4203fd5e2	ee3d80cb6	0	1	0	0	0	0	0	0	1	0	0	0	0	0	2
1088	ID_7c33c1884	a0695cb68	0	0	0	0	1	0	0	0	0	0	0	0	1	0	1
1089	ID_77cce5b75	62c28e034	1	0	0	0	0	0	0	0	0	1	0	0	0	0	4
1090	ID_df05b9e45	62c28e034	1	0	0	0	0	0	0	0	0	1	0	0	0	0	4
1091	ID_3490fd704	8e284abd5	1	0	0	0	0	0	0	0	0	1	0	0	0	0	4
1092	ID_d82b1a426	8e284abd5	1	0	0	0	0	0	0	0	0	1	0	0	0	0	4
1093	ID_9d6957e8a	8e284abd5	1	0	0	0	0	0	0	0	0	1	0	0	0	0	4
1094	ID_5038a636a	304731467	1	0	0	0	0	0	0	0	1	0	0	0	0	0	2
1095	ID_6c29eea22	304731467	1	0	0	0	0	0	0	0	1	0	0	0	0	0	2
1096	ID_870ae3993	304731467	1	0	0	0	0	0	0	0	1	0	0	0	0	0	2
1097	ID_00da43675	304731467	1	0	0	0	0	0	0	0	1	0	0	0	0	0	2
1098	ID_22d124fdf	304731467	1	0	0	0	0	0	0	0	1	0	0	0	0	0	2
1099	ID_075c52143	304731467	1	0	0	0	0	0	0	0	1	0	0	0	0	0	2

```
is pertaining to house material quality. Columns 38-41, 42, 65-67, 68-70, 71-73

.loc[:, ["techozinc", "techoentrepiso", "techocane", "techootro", "cielorazo", "epared1", "epared2", "epared3", "etecho1", "etecho2", "etecho3", "eviv1", "eviv2", "eviv3", "Target"]].iloc[0: 60]
.loc[:, ["techozinc", "techoentrepiso", "techocane", "techootro", "cielorazo", "epared1", "epared2", "epared3", "etecho1", "etecho2", "etecho3", "eviv1", "eviv2", "eviv3", "Target"]].iloc[1050: 1100]
.loc[:, ["Id", "idhogar", "techozinc", "techoentrepiso", "techocane", "techootro", "cielorazo", "epared1", "epared2", "epared3", "etecho1", "etecho2", "etecho3", "eviv1", "eviv2", "eviv3", "Target"]].iloc[1086: 1100]
```

	Id	idhogar	techozinc	techoentrepiso	techocane	techootro	cielorazo	epared1	epared2	epared3	etecho1	etecho2	etecho3	eviv1	eviv2	eviv3	Target
1086	ID_30d6500c3	2e65e4af3	1	0	0	0	1	0	0	1	0	0	1	0	0	1	4
1087	ID_4203fd5e2	ee3d80cb6	1	0	0	0	1	0	0	1	0	0	1	0	0	1	2
1088	ID_7c33c1884	a0695cb68	1	0	0	0	1	0	0	1	0	0	1	0	0	1	1
1089	ID_77cce5b75	62c28e034	1	0	0	0	1	0	0	1	0	0	1	0	0	1	4
1090	ID_df05b9e45	62c28e034	1	0	0	0	1	0	0	1	0	0	1	0	0	1	4
1091	ID_3490fd704	8e284abd5	1	0	0	0	0	0	1	0	0	0	1	0	1	0	4
1092	ID_d82b1a426	8e284abd5	1	0	0	0	0	0	1	0	0	0	1	0	1	0	4
1093	ID_9d6957e8a	8e284abd5	1	0	0	0	0	0	1	0	0	0	1	0	1	0	4
1094	ID_5038a636a	304731467	1	0	0	0	1	0	1	0	0	1	0	0	1	0	2
1095	ID_6c29eea22	304731467	1	0	0	0	1	0	1	0	0	1	0	0	1	0	2
1096	ID_870ae3993	304731467	1	0	0	0	1	0	1	0	0	1	0	0	1	0	2
1097	ID_00da43675	304731467	1	0	0	0	1	0	1	0	0	1	0	0	1	0	2
1098	ID_22d124fdf	304731467	1	0	0	0	1	0	1	0	0	1	0	0	1	0	2
1099	ID_075c52143	304731467	1	0	0	0	1	0	1	0	0	1	0	0	1	0	2

## Columns pertaining to necessary facilities and appliances for good life quality

```
g to necessary facilities and appliances for good life quality. 7, 43-45, 46-49, 50-54
```

```
["Id", "idhogar", "refrig", "abastaguadentro", "abastaguafuera", "abastaguano", "public", "planpri", "noelec", "coopele", "sanitario1", "sanitario2", "sanitario3", "sanitario5", "sanitario6", "Target"]].iloc[1086: 1100]
```

✓ 0.1s

Python

	Id	idhogar	refrig	abastaguadentro	abastaguafuera	abastaguano	public	planpri	noelec	coopele	sanitario1	sanitario2	sanitario3	sanitario5	sanitario6	Target
1086	ID_30d6500c3	2e65e4af3	1	1	0	0	1	0	0	0	0	1	0	0	0	4
1087	ID_4203fd5e2	ee3d80cb6	1	1	0	0	1	0	0	0	0	0	1	0	0	2
1088	ID_7c33c1884	a0695cb68	1	1	0	0	1	0	0	0	0	0	1	0	0	1
1089	ID_77cce5b75	62c28e034	1	1	0	0	1	0	0	0	0	0	1	0	0	4
1090	ID_dff05b9e45	62c28e034	1	1	0	0	1	0	0	0	0	0	1	0	0	4
1091	ID_3490fd704	8e284abd5	1	1	0	0	1	0	0	0	0	0	1	0	0	4
1092	ID_d82b1a426	8e284abd5	1	1	0	0	1	0	0	0	0	0	1	0	0	4
1093	ID_9d6957e8a	8e284abd5	1	1	0	0	1	0	0	0	0	0	1	0	0	4
1094	ID_5038a636a	304731467	1	1	0	0	1	0	0	0	0	0	1	0	0	2
1095	ID_6c29eea22	304731467	1	1	0	0	1	0	0	0	0	0	1	0	0	2
1096	ID_870ae3993	304731467	1	1	0	0	1	0	0	0	0	0	1	0	0	2
1097	ID_00da43675	304731467	1	1	0	0	1	0	0	0	0	0	1	0	0	2
1098	ID_22d124fdf	304731467	1	1	0	0	1	0	0	0	0	0	1	0	0	2
1099	ID_075c52143	304731467	1	1	0	0	1	0	0	0	0	0	1	0	0	2

```
# Columns pertaining to necessary facilities and appliances for good life quality. 55-58, 59-64
```

```
trainDF.loc[:, ["Id", "idhogar", "energocinar1", "energocinar2", "energocinar3", "energocinar4", "elimbasu1", "elimbasu2", "elimbasu3", "elimbasu4", "elimbasu5", "elimbasu6", "Target"]].iloc[1086: 1100]
```

✓ 0.1s

Python

	Id	idhogar	energocinar1	energocinar2	energocinar3	energocinar4	elimbasu1	elimbasu2	elimbasu3	elimbasu4	elimbasu5	elimbasu6	Target
1086	ID_30d6500c3	2e65e4af3	0	1	0	0	1	0	0	0	0	0	4
1087	ID_4203fd5e2	ee3d80cb6	0	1	0	0	1	0	0	0	0	0	2
1088	ID_7c33c1884	a0695cb68	0	0	1	0	1	0	0	0	0	0	1
1089	ID_77cce5b75	62c28e034	0	1	0	0	1	0	0	0	0	0	4
1090	ID_dff05b9e45	62c28e034	0	1	0	0	1	0	0	0	0	0	4
1091	ID_3490fd704	8e284abd5	0	1	0	0	1	0	0	0	0	0	4
1092	ID_d82b1a426	8e284abd5	0	1	0	0	1	0	0	0	0	0	4
1093	ID_9d6957e8a	8e284abd5	0	1	0	0	1	0	0	0	0	0	4
1094	ID_5038a636a	304731467	0	1	0	0	1	0	0	0	0	0	2
1095	ID_6c29eea22	304731467	0	1	0	0	1	0	0	0	0	0	2
1096	ID_870ae3993	304731467	0	1	0	0	1	0	0	0	0	0	2
1097	ID_00da43675	304731467	0	1	0	0	1	0	0	0	0	0	2
1098	ID_22d124fdf	304731467	0	1	0	0	1	0	0	0	0	0	2
1099	ID_075c52143	304731467	0	1	0	0	1	0	0	0	0	0	2

## Columns pertaining to education

```
# Columns pertaining to education. Columns 21-22, 105-113
```

```
trainDF.loc[:, ["Id", "idhogar", "escolar1", "rez_esc", "instlevel1", "instlevel2", "instlevel3", "instlevel4", "instlevel5", "instlevel6", "instlevel7", "instlevel8", "instlevel9", "Target"]].iloc[1086: 1100]
```

✓ 0.1s

Python

	Id	idhogar	escolar1	rez_esc	instlevel1	instlevel2	instlevel3	instlevel4	instlevel5	instlevel6	instlevel7	instlevel8	instlevel9	Target
1086	ID_30d6500c3	2e65e4af3	9	NaN	0	0	0	1	0	0	0	0	0	4
1087	ID_4203fd5e2	ee3d80cb6	7	NaN	0	0	0	1	0	0	0	0	0	2
1088	ID_7c33c1884	a0695cb68	16	NaN	0	0	0	0	0	0	0	1	0	1
1089	ID_77cce5b75	62c28e034	3	NaN	0	1	0	0	0	0	0	0	0	4
1090	ID_dff05b9e45	62c28e034	2	NaN	0	1	0	0	0	0	0	0	0	4
1091	ID_3490fd704	8e284abd5	11	NaN	0	0	0	0	0	1	0	0	0	4
1092	ID_d82b1a426	8e284abd5	9	NaN	0	0	0	0	0	1	0	0	0	4
1093	ID_9d6957e8a	8e284abd5	11	NaN	0	0	0	0	1	0	0	0	0	4
1094	ID_5038a636a	304731467	7	NaN	0	0	0	1	0	0	0	0	0	2
1095	ID_6c29eea22	304731467	0	NaN	1	0	0	0	0	0	0	0	0	2
1096	ID_870ae3993	304731467	6	NaN	0	0	1	0	0	0	0	0	0	2
1097	ID_00da43675	304731467	5	0.0	0	1	0	0	0	0	0	0	0	2
1098	ID_22d124fdf	304731467	8	NaN	0	0	0	1	0	0	0	0	0	2
1099	ID_075c52143	304731467	8	NaN	0	0	0	1	0	0	0	0	0	2

Columns pertaining to household heads

# Columns pertaining to household heads. Columns 102-104, 77-83

trainDF.loc[:, ["Id", "idhogar", "edjefe", "edjefa", "meaneduc", "estadocivil1", "estadocivil2", "estadocivil3", "estadocivil4", "estadocivil5", "estadocivil6", "estadocivil7", "Target"]].iloc[1086: 1100]

✓ 0.1s

Python

	Id	idhogar	edjefe	edjefa	meaneduc	estadocivil1	estadocivil2	estadocivil3	estadocivil4	estadocivil5	estadocivil6	estadocivil7	Target
1086	ID_30d6500c3	2e65e4af3	11	no	9.250000	0	0	0	1	0	0	0	4
1087	ID_4203fd5e2	ee3d80cb6	7	no	7.000000	0	0	0	0	1	0	0	2
1088	ID_7c33c1884	a0695cb68	no	16	16.000000	0	0	0	0	0	1	0	1
1089	ID_77cce5b75	62c28e034	no	2	2.500000	0	0	0	0	1	0	0	4
1090	ID_df05b9e45	62c28e034	no	2	2.500000	0	0	0	1	0	0	0	4
1091	ID_3490fd704	8e284abd5	no	9	10.333333	0	1	0	0	0	0	0	4
1092	ID_d82b1a426	8e284abd5	no	9	10.333333	0	0	0	1	0	0	0	4
1093	ID_9d6957e8a	8e284abd5	no	9	10.333333	0	1	0	0	0	0	0	4
1094	ID_5038a636a	304731467	8	no	14.500000	0	0	0	0	0	0	1	2
1095	ID_6c29eea22	304731467	8	no	14.500000	1	0	0	0	0	0	0	2
1096	ID_870ae3993	304731467	8	no	14.500000	0	0	1	0	0	0	0	2
1097	ID_00da43675	304731467	8	no	14.500000	0	0	0	0	0	0	1	2
1098	ID_22d124fdf	304731467	8	no	14.500000	0	0	0	0	0	0	1	2
1099	ID_075c52143	304731467	8	no	14.500000	0	0	1	0	0	0	0	2

Columns pertaining to home location

# Columns pertaining to household heads. Columns 125-130, 131-132

trainDF.loc[:, ["Id", "idhogar", "lugar1", "lugar2", "lugar3", "lugar4", "lugar5", "lugar6", "area1", "area2", "Target"]].iloc[1086: 1100]

✓ 0.0s

	Id	idhogar	lugar1	lugar2	lugar3	lugar4	lugar5	lugar6	area1	area2	Target
1086	ID_30d6500c3	2e65e4af3	1	0	0	0	0	0	1	0	4
1087	ID_4203fd5e2	ee3d80cb6	1	0	0	0	0	0	1	0	2
1088	ID_7c33c1884	a0695cb68	1	0	0	0	0	0	1	0	1
1089	ID_77cce5b75	62c28e034	1	0	0	0	0	0	1	0	4
1090	ID_df05b9e45	62c28e034	1	0	0	0	0	0	1	0	4
1091	ID_3490fd704	8e284abd5	1	0	0	0	0	0	1	0	4
1092	ID_d82b1a426	8e284abd5	1	0	0	0	0	0	1	0	4
1093	ID_9d6957e8a	8e284abd5	1	0	0	0	0	0	1	0	4
1094	ID_5038a636a	304731467	1	0	0	0	0	0	1	0	2
1095	ID_6c29eea22	304731467	1	0	0	0	0	0	1	0	2
1096	ID_870ae3993	304731467	1	0	0	0	0	0	1	0	2
1097	ID_00da43675	304731467	1	0	0	0	0	0	1	0	2
1098	ID_22d124fdf	304731467	1	0	0	0	0	0	1	0	2
1099	ID_075c52143	304731467	1	0	0	0	0	0	1	0	2

## Columns pertaining to electronics

```
# Columns pertaining to household heads. Columns 121-124, 8-9
```

```
trainDF.loc[:, ["Id", "idhogar", "computer", "television", "mobilephone", "qmobilephone", "v18q", "v18q1", "Target"]].iloc[1086: 1100]
```

[234] ✓ 0.1s

	Id	idhogar	computer	television	mobilephone	qmobilephone	v18q	v18q1	Target
1086	ID_30d6500c3	2e65e4af3	0	0	1	7	1	1.0	4
1087	ID_4203fd5e2	ee3d80cb6	0	1	1	1	0	NaN	2
1088	ID_7c33c1884	a0695cb68	0	0	1	1	0	NaN	1
1089	ID_77cce5b75	62c28e034	0	0	0	0	0	NaN	4
1090	ID_df05b9e45	62c28e034	0	0	0	0	0	NaN	4
1091	ID_3490fd704	8e284abd5	0	1	1	6	0	NaN	4
1092	ID_d82b1a426	8e284abd5	0	1	1	6	0	NaN	4
1093	ID_9d6957e8a	8e284abd5	0	1	1	6	0	NaN	4
1094	ID_5038a636a	304731467	0	0	1	4	1	1.0	2
1095	ID_6c29eea22	304731467	0	0	1	4	1	1.0	2
1096	ID_870ae3993	304731467	0	0	1	4	1	1.0	2
1097	ID_00da43675	304731467	0	0	1	4	1	1.0	2
1098	ID_22d124fdf	304731467	0	0	1	4	1	1.0	2
1099	ID_075c52143	304731467	0	0	1	4	1	1.0	2

```
# If all families have the same poverty level, this value should be 1.0
print(sumofNormAverages / len(homelist))
```

[234] ✓ 3.6s

Python

1.0009487746561039

```
# Output the list of homes with inconsistent poverty levels. Output its length, too
print(len(inconsistentPovertyHomes))
print(inconsistentPovertyHomes)
```

[234] ✓ 0.5s

Python

85

```
['4b6077882', '6833ac5dc', '43b9c83e5', '5c3f7725d', '0f9494d3a', 'daafc1281', '73d85d05d', 'bcas2e2f5', '44f219a16', 'efd3aec61', '3c6973219', '0511912b6', 'f006348ed', 'a20ff33ba', '5e9329fc6', 'e65d4b943', '42ec8bef5', '6bcf799cf', '26b3a0f41', '4dc11e11f', '594d3eb27', 'd9b1558b5', '7ea6aca15', '8bb6da3c1', '3df651058', '811a35744', '2cb443214', 'bcab69521', '694a0cbf4', '3fe29a56b', '636330516', '288579c97', '15a891635', '6a389f3de', 'a3288e6fa', '4e19bd549', '80a66379b', '5c6f32bbc', '932287f5d', 'bd82509d1', '614b48fb7', '46af47063', '6c543442a', '410194c8b', '417865404', 'f7b421c2c', '67ad49822', '17fb04a62', 'c38913488', '513adb616', 'dfb966eec', '30a70901d', '18832b040', '7c57f8237', 'c13325faf', '54118d5d9', '0f3e65c83', '03f4e5f4d', '8ae3e74ca', '309fb7246', '09e25d616', '564eab113', '8242a51ec', '0172ab1d9', 'a94a45642', 'be91da044', '50e064ee8', '4c2dba109', '7ad269eef', '3c73c107f', '55a662731', 'e17b252ed', '078a0b6e2', '28893b5e7', 'd64524b6b', '2c9872b82', 'f94589d38', '8420bcfca', '71cd52a80', '654ef7612', 'cc971b690', '7e9d58c5c', 'e235a4eec', 'c7ce4e38c', '9bbf7c6ca']
```

```
# Print the list of families without heads
print(len(familiesMOutHeads))
print(familiesMOutHeads)
```

[233] ✓ 0.0s

Python

15

```
['09b195e7a', '89fe6d3e', '61c10e099', '374ca5a19', 'bfd5067c2', '1367ab31d', '6b1b2405f', 'f2bfa75c4', '03c6bdF85', 'ad687ad89', 'b1f4d89d7', 'c0c8a5013', 'a0812ef17', 'd363d9183', '1bc617b23']
```

```
# We must fill all the NaN values in the dataset. First, determine which columns have NaN values.
```

```
for column in X.columns:  
    if(X[column].isna().any() == True):  
        print(column)
```

✓ 0.1s

```
v2a1  
v18q1  
rez_esc  
meaneduc  
SQBmeaned
```

```
rf_class = RandomForestClassifier(n_estimators = 10)
```

✓ 0.0s

```
# Use cross validation with 10 iterations???? This is where the random forest classifier comes into play  
cvResult = cross_val_score(rf_class, dataInput, dataOutput, scoring = "accuracy", cv = 10)  
print(cvResult)
```

✓ 2.4s

```
[0.61192469 0.64330544 0.67154812 0.61610879 0.64330544 0.62970711  
0.56171548 0.51623037 0.49842932 0.55287958]
```

```
# Check how accurate the cross-validation result is in terms of a percentage.  
accuracy = cvResult.mean() * 100  
print("Accuracy of the random forest classifier is ", accuracy)
```

✓ 0.0s

```
Accuracy of the random forest classifier is 59.45154329777213
```