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## Regis University

### MSDS 621

## Week 5 Lab: EDA and Visualizations

This week's assignment will be combining many of the concepts from our prior lectures.

Below, I've loaded the immunization dataset from week 3 (nispuf14.csv). You can feel free to use your output from week3 or the verse I have provided in the assign\_wk5 folder.

Here is what I've demonstrated below with the immunization dataset.

- separated continuous and categorical columns
- minimally handled NaNs
- built a baseline RandomForestClassifier with a random column

I've selected FRSTBRN as my target variable target variable -- not a very interesting column, but it had no missing values. Do not worry, you will have a chance to improve on my work.

```
In [1]: import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

# Makes graphs prettier
sns.set()
# Magic command for plots
%matplotlib inline
```

**Note::** There are a couple of new parameters I'm using with read\_csv. I encourage you to go look those up and understand what they do.

## Load the data

```
In [2]: df = pd.read_csv("assign_wk5/nispuf14.csv", na_values=['.'], low_memory=False)
```

```
In [3]: df.head()
```

```
Out[3]:
```

	SEQNUMC	SEQNUMHH	PDAT	PROVWT_D	PROVWT_D_TERR	RDDWT_D	f
0	11	1	2	.	.	218.30024855484000	
1	21	2	1	806.84601169505000	806.84601169505000	454.86041741251200	
2	31	3	2	.	.	30.54542540283290	
3	41	4	1	63.44868567610260	63.44868567610260	36.96593137368630	
4	51	5	1	94.87263225744540	94.87263225744540	64.62020426239790	

5 rows × 461 columns

**Pop Quiz::** What am I doing in the cell below?

```
In [4]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 24897 entries, 0 to 24896
Columns: 461 entries, SEQNUMC to INS_11
dtypes: float64(220), int64(29), object(212)
memory usage: 87.6+ MB
```

Answer: All of the various formats that can be numeric are being made numeric, with the call to prevent it from telling you have the cells that can not be changed into numbers not throwing a warning.

```
In [5]: for col in df.columns:
         df[col] = pd.to_numeric(df[col], errors='coerce')
```

```
In [6]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 24897 entries, 0 to 24896
Columns: 461 entries, SEQNUMC to INS_11
dtypes: float64(432), int64(29)
memory usage: 87.6 MB
```

```
In [7]: df.head()
```

```
Out[7]:
```

	SEQNUMC	SEQNUMHH	PDAT	PROVWT_D	PROVWT_D_TERR	RDDWT_D	RDDWT_D_TERR	SI
0	11	1	2	NaN	NaN	218.300249	218.300249	
1	21	2	1	806.846012	806.846012	454.860417	454.860417	
2	31	3	2	NaN	NaN	30.545425	30.545425	
3	41	4	1	63.448686	63.448686	36.965931	36.965931	
4	51	5	1	94.872632	94.872632	64.620204	64.620204	

5 rows × 461 columns

I like to make a copy of my dataset before I start manipulating the data. This is a personal preference.

```
In [8]: df_copy = df.copy()
```

```
In [9]: !pip install PyPDF2
```

```
Defaulting to user installation because normal site-packages is not writeable
Requirement already satisfied: PyPDF2 in c:\users\matth\appdata\roaming\python\python310\site-packages (3.0.1)
```

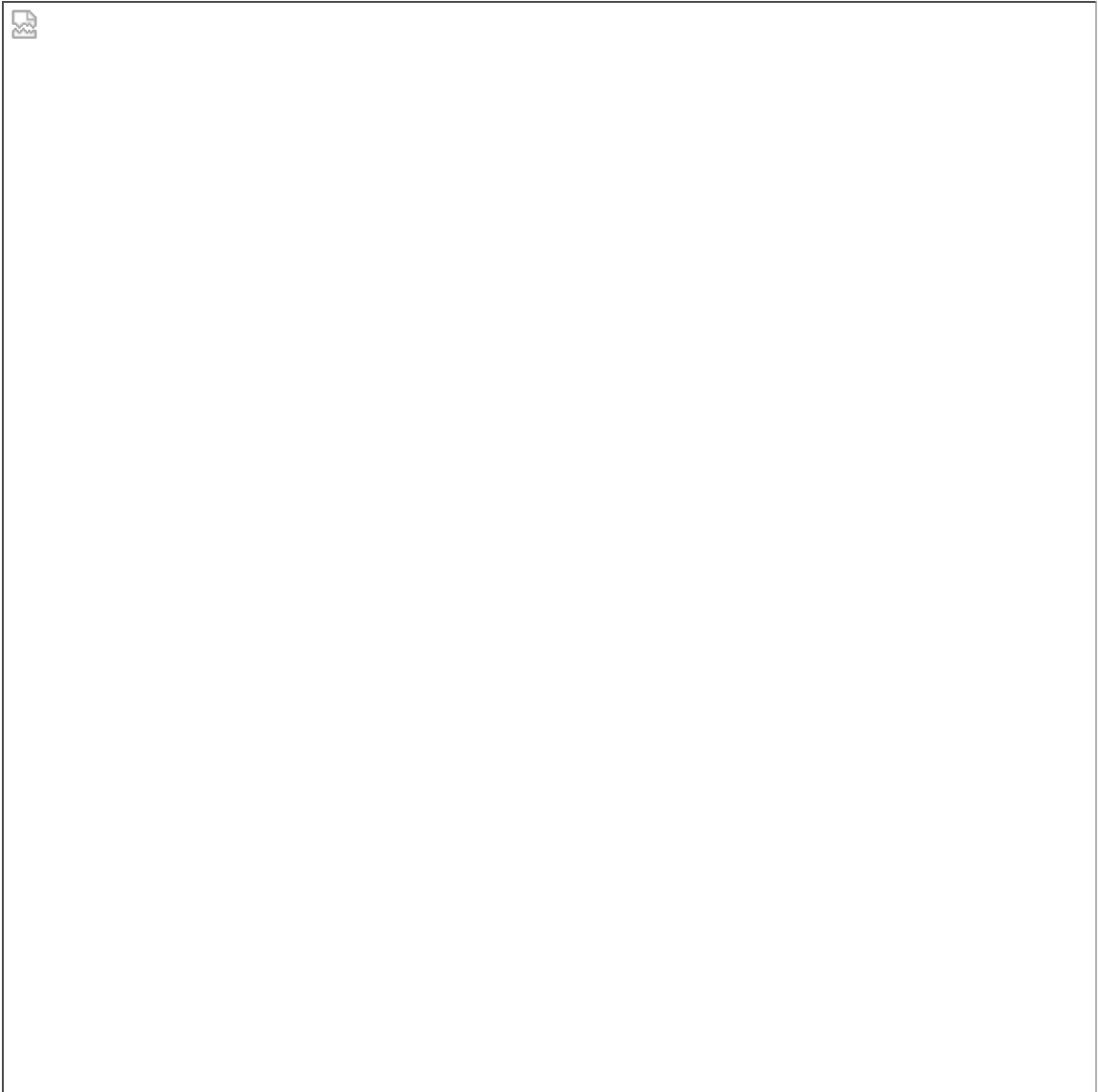
## Seperate Categorical vs Continuous Variables

```
In [10]: from PyPDF2 import PdfReader
         #from PyPdf2.pdf import Destination # read the pdf file
```

```
In [11]: pdf_file = 'assign_wk5/NISPUF14_CODEBOOK.PDF'
```

```
In [12]: reader = PdfReader(pdf_file)
         outlines = reader.outline
```

I notice the PDF's outline tells us which variables are continuous. I would like to be able to read that outline and get those variables. Unfortunately, the PDF outline format is not terribly conducive to this operation.



As you can see, in the outline "tree", when we see the text "Continuous Statistics", we need the **previous** entry, but PDF outlines are weird mixes of dictionaries and lists. I finally found the following answer on StackOverflow that satisfied the need.

From <https://stackoverflow.com/questions/1011938/python-previous-and-next-values-inside-a-loop>

```
In [13]: from itertools import tee, islice, chain

def previous_and_next(some_iterable):
    prevs, items, nexts = tee(some_iterable, 3)
    prevs = chain([None], prevs)
    nexts = chain(islice(nexts, 1, None), [None])
    return zip(prevs, items, nexts)
```

Testing if I could find the word "Continuous" in the PDF outline.

```
In [14]: 'Continuous' in outlines[7][0].title
```

```
Out[14]: True
```

```
In [15]: cont_list = []
for prev, item, nxt in previous_and_next(outlines):
    if isinstance(item, list):
        if 'Continuous' in str(item[0].title):
            cont_list.append(prev.title)
```

```
In [16]: cont_list[:5]
```

```
Out[16]: ['PROVWT_D', 'PROVWT_D_TERR', 'RDDWT_D', 'RDDWT_D_TERR', 'BF_ENDR06']
```

```
In [17]: cat_list = [c for c in df_copy.columns if c not in cont_list]
```

## Cleaning up the Missing Values

I'm not going to do a lot to handle the missing values in this demo. **However**, I will expect you to do more than I do.

I'll simply:

- for categories, fill with -999
- for continuous, fill with mean

```
In [18]: for col in cat_list:
df_copy[col].fillna(-999, inplace=True)
```

```
In [19]: for col in cont_list:
df_copy[col].fillna(df[col].mean(), inplace=True)
```

```
In [20]: df_copy.head()
```

```
Out[20]:
```

	SEQNUMC	SEQNUMHH	PDAT	PROVWT_D	PROVWT_D_TERR	RDDWT_D	RDDWT_D_TERR	SI
0	11	1	2	383.438950	382.821312	218.300249	218.300249	
1	21	2	1	806.846012	806.846012	454.860417	454.860417	
2	31	3	2	383.438950	382.821312	30.545425	30.545425	
3	41	4	1	63.448686	63.448686	36.965931	36.965931	
4	51	5	1	94.872632	94.872632	64.620204	64.620204	

5 rows × 461 columns

# Random Forest Classifier Benchmark

My target is going to be FRSTBRN -- FIRST BORN STATUS OF CHILD.

FRSTBRN is a categorical variable (1 - No, 2 - Yes), so I will use the classifier version of RandomForest. If your target variable is continuous, you will need to use the regressor version of this algorithm.

Take a look at:

<https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html>

<https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestRegressor.html>

```
In [21]: from sklearn.model_selection import train_test_split
        from sklearn.ensemble import RandomForestClassifier
```

**Pop Quiz::** Do you know what the following does?

Answer: The computer uses a random seed for splitting the test and train set. This means that each time the program is run a different set is created. If we want to be able to replicated our results the seed must be set. Which number should be used. 42, of course.

See Hitch Hikers Guide to the Galaxy, Douglas Adams

```
In [22]: np.random.seed(42)
```

```
In [23]: y = df_copy['FRSTBRN']
        X = df_copy.drop('FRSTBRN', axis=1)
```

I'm going to get the min and max values from one of the continuous variables to use as the min/max for the random column.

```
In [24]: the_min = X.PROVWT_D.min()
        the_max = X.PROVWT_D.max()
        X['random'] = np.random.normal(the_min, the_max, size=X.shape[0])
```

```
In [25]: x_train,x_test,y_train,y_test=train_test_split(X,y,test_size=0.3)
```

```
In [26]: clf=RandomForestClassifier(n_estimators=100)
```

```
In [27]: clf.fit(x_train,y_train)
```

```
Out[27]: ▼ RandomForestClassifier
        RandomForestClassifier()
```

I'm going to check the accuracy of my model. Ultimately we want to use this model to help us learn something about our data. So, if our model's accuracy is low, then our "learning" will have a low level of confidence too.

```
In [28]: y_pred=clf.predict(x_test)
```

```
In [29]: from sklearn import metrics
```

```
In [30]: print("Accuracy:", metrics.accuracy_score(y_test, y_pred))
```

Accuracy: 0.8832663989290496

A model with a 88% accuracy is really good. One technique you can use to increase your accuracy is scale/normalize your data. The reasoning behind this is that algorithms like Random Forest tend to "favor" columns with a large range of values. Scaling/Normalizing your data will reduce this bias effect in your algorithm.

<https://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.StandardScaler.html>

<https://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.normalize.html>

## Feature Selection: Random Number Trick

```
In [31]: features = x_train.columns
importances = clf.feature_importances_
std = np.std([tree.feature_importances_ for tree in clf.estimators_],
              axis=0)
indices = np.argsort(importances)[::-1]

feature_rank = []
# Print the feature ranking
print("Feature ranking:")

for f in range(x_train.shape[1]):
    feature = f"{f + 1}. feature {features[indices[f]]} \t{importances[indices[f]]}"
    if 'random' in features[indices[f]]:
        feature += " <=="
    print(feature)
    feature_rank.append([features[indices[f]], importances[indices[f]]])
```

## Feature ranking:

1. feature CHILDNM	27.04%	
2. feature C1R	15.07%	
3. feature random	1.72%	<==
4. feature SEQNUMC	1.61%	
5. feature RDDWT_D_TERR		1.59%
6. feature SEQNUMHH	1.58%	
7. feature RDDWT_D	1.53%	
8. feature STRATUM	1.46%	
9. feature INCPORAR	1.41%	
10. feature M_AGEGRP	1.32%	
11. feature BF_ENDR06		1.27%
12. feature EST_GRANT		1.27%
13. feature ESTIAP14	1.24%	
14. feature STATE	1.18%	
15. feature BF_FORMR08		1.06%
16. feature INCQ298A	1.02%	
17. feature BF_EXCLR06		0.99%
18. feature NUM_CELLS_HH		0.74%
19. feature AGEGRP	0.70%	
20. feature EDUC1	0.66%	
21. feature D6R	0.61%	
22. feature PROVWT_D	0.60%	
23. feature PROVWT_D_TERR		0.58%
24. feature INCPOV1	0.58%	
25. feature C5R	0.56%	
26. feature DDTP4	0.51%	
27. feature CEN_REG	0.51%	
28. feature INTRP	0.50%	
29. feature DVRC1	0.49%	
30. feature NUM_CELLS_PARENTS		0.49%
31. feature DHEPB2	0.48%	
32. feature DHIB3	0.48%	
33. feature DDTP3	0.48%	
34. feature DFLU2	0.48%	
35. feature DHIB4	0.48%	
36. feature DPCV4	0.48%	
37. feature RACEETHK	0.47%	
38. feature DHEPB3	0.47%	
39. feature DHEPA2	0.47%	
40. feature DMMR1	0.46%	
41. feature DHEPA1	0.45%	
42. feature DFLU1	0.45%	
43. feature DPOLIO3	0.45%	
44. feature DDTP2	0.44%	
45. feature DPOLIO2	0.44%	
46. feature DPCV3	0.44%	
47. feature RENT_OWN	0.44%	
48. feature DDTP1	0.43%	
49. feature DHIB1	0.42%	
50. feature DHIB2	0.42%	
51. feature DPCV2	0.42%	
52. feature MARITAL2	0.41%	
53. feature DROT2	0.41%	
54. feature CWIC_02	0.40%	
55. feature DROT1	0.39%	
56. feature DFLU3	0.38%	
57. feature DPOLIO1	0.38%	
58. feature RACE_K	0.38%	



59. feature DPCV1	0.37%	
60. feature SEX	0.35%	
61. feature NUM_PHONE		0.34%
62. feature DROT3	0.34%	
63. feature FLU1_AGE	0.31%	
64. feature FLU2_AGE	0.30%	
65. feature FLU3_AGE	0.30%	
66. feature DHEPB1	0.29%	
67. feature HEA2_AGE	0.29%	
68. feature INS_1	0.29%	
69. feature DTP4_AGE	0.29%	
70. feature CWIC_01	0.26%	
71. feature HEP3_AGE	0.26%	
72. feature INS_2	0.26%	
73. feature HIB4_AGE	0.25%	
74. feature HEA1_AGE	0.25%	
75. feature INS_3	0.24%	
76. feature PCV4_AGE	0.24%	
77. feature P_NUMFLU	0.23%	
78. feature INS_4_5	0.22%	
79. feature INS_11	0.22%	
80. feature CBF_01	0.22%	
81. feature MOBIL_I	0.22%	
82. feature INS_3A	0.21%	
83. feature I_HISP_K	0.21%	
84. feature MMR1_AGE	0.21%	
85. feature INS_6	0.20%	
86. feature HIB3_AGE	0.20%	
87. feature P_NUMFLUN		0.20%
88. feature VRC1_AGE	0.20%	
89. feature DHEPB4	0.19%	
90. feature LANGUAGE	0.19%	
91. feature HEP2_AGE	0.19%	
92. feature P_NUHIBX	0.19%	
93. feature DFLU4	0.18%	
94. feature DTP3_AGE	0.18%	
95. feature PROV_FAC	0.18%	
96. feature P_NUMHS	0.17%	
97. feature P_NUMDTA	0.17%	
98. feature P_NUMDIH	0.16%	
99. feature REGISTRY	0.16%	
100. feature DPOLIO4	0.15%	
101. feature D7	0.15%	
102. feature POL3_AGE		0.15%
103. feature PCV3_AGE		0.15%
104. feature FLU4_AGE		0.15%
105. feature P_NUHEPX		0.14%
106. feature P_NUMHM	0.14%	
107. feature P_NUMHEA		0.14%
108. feature POL4_AGE		0.13%
109. feature HIB2_AGE		0.13%
110. feature POL2_AGE		0.13%
111. feature DTP2_AGE		0.13%
112. feature VFC_ORDER		0.13%
113. feature ROT3_AGE		0.13%
114. feature P_NUMDHI		0.12%
115. feature ROT2_AGE		0.12%
116. feature P_NUMIPV		0.12%
117. feature PCV2_AGE		0.12%

118.	feature	XPOLTY3	0.12%	
119.	feature	HEP4_AGE		0.11%
120.	feature	ROT1_AGE		0.11%
121.	feature	XPOLTY1	0.11%	
122.	feature	P_NUMRM	0.11%	
123.	feature	N_PRVR	0.11%	
124.	feature	PCV1_AGE		0.11%
125.	feature	P_NUMHEP		0.10%
126.	feature	DTP1_AGE		0.10%
127.	feature	P_NUMROT		0.10%
128.	feature	XPOLTY2	0.10%	
129.	feature	HEP1_AGE		0.10%
130.	feature	XDTPTY1	0.10%	
131.	feature	POL1_AGE		0.10%
132.	feature	P_NUMRG	0.10%	
133.	feature	XDTPTY2	0.09%	
134.	feature	U1D_HEP	0.09%	
135.	feature	HIB1_AGE		0.09%
136.	feature	XDTPTY4	0.09%	
137.	feature	XDTPTY3	0.08%	
138.	feature	P_NUMPCC13		0.08%
139.	feature	P_UTDHEPA2		0.08%
140.	feature	AGECPOXR		0.08%
141.	feature	HAD_CPOX		0.08%
142.	feature	P_NUMHIB		0.08%
143.	feature	P_NUMHIN		0.08%
144.	feature	XHEPTY2	0.08%	
145.	feature	P_NUMPOL		0.08%
146.	feature	XHEPTY3	0.07%	
147.	feature	HEP_BRTH		0.07%
148.	feature	P_NUMPCC		0.07%
149.	feature	U3D_HEP	0.07%	
150.	feature	P_NUMFLUM		0.07%
151.	feature	U2D_HEP	0.07%	
152.	feature	XHEPTY4	0.06%	
153.	feature	P_NUMVRX		0.06%
154.	feature	P_NUMPCV		0.06%
155.	feature	P_NUMMMRX		0.06%
156.	feature	XHEPTY1	0.05%	
157.	feature	P_UTDROT_S		0.05%
158.	feature	P_NUMDTP		0.05%
159.	feature	P_UTD431H314_ROUT_S		0.05%
160.	feature	P_UTD431H313_ROUT_S		0.04%
161.	feature	P_UTD431	0.04%	
162.	feature	XMMRTY1	0.04%	
163.	feature	P_UTD431H31_ROUT_S		0.04%
164.	feature	P_NUMVRC		0.04%
165.	feature	P_NUMRO	0.04%	
166.	feature	P_NUMMMR		0.04%
167.	feature	P_UTD431H_ROUT_S		0.04%
168.	feature	PU431_314		0.04%
169.	feature	P_NUMMRV		0.04%
170.	feature	XPCVTY4	0.04%	
171.	feature	P_UTDHEPA1		0.04%
172.	feature	XPCVTY1	0.04%	
173.	feature	P_UTDHIB_ROUT_S		0.04%
174.	feature	P_NUMPCN		0.04%
175.	feature	P_UTDTP4		0.04%
176.	feature	PU4313314		0.04%

177.	feature	XPOLTY4	0.04%	
178.	feature	P_UTD431H3_ROUT_S		0.04%
179.	feature	P_NUMMMX	0.04%	
180.	feature	XPCVTY2	0.04%	
181.	feature	PU431331	0.04%	
182.	feature	P_NUMPCC7	0.04%	
183.	feature	MMR2_AGE	0.03%	
184.	feature	DMMR2	0.03%	
185.	feature	PU4313313	0.03%	
186.	feature	P_NUMFLUL	0.03%	
187.	feature	VRC2_AGE	0.03%	
188.	feature	PU431_31	0.03%	
189.	feature	P_UTDHEP	0.03%	
190.	feature	PUT43133	0.03%	
191.	feature	XPCVTY3	0.03%	
192.	feature	P_UTDPCV	0.03%	
193.	feature	DVRC2	0.03%	
194.	feature	P_NUMTPN	0.03%	
195.	feature	P_NUMOLN	0.03%	
196.	feature	PUTD4313	0.03%	
197.	feature	P_U12VRC	0.03%	
198.	feature	DHIB5	0.03%	
199.	feature	DFLU5	0.02%	
200.	feature	DTP5_AGE	0.02%	
201.	feature	P_NUMHG	0.02%	
202.	feature	P_UTDHIB	0.02%	
203.	feature	P_NUMHION	0.02%	
204.	feature	P_NUMHHY	0.02%	
205.	feature	DDTP5	0.02%	
206.	feature	P_UTDMMX	0.02%	
207.	feature	HIB5_AGE	0.02%	
208.	feature	P_UTDMCV	0.02%	
209.	feature	P_NUMHEN	0.02%	
210.	feature	PCV5_AGE	0.02%	
211.	feature	P_NUMDAH	0.02%	
212.	feature	P_UTDPOL	0.02%	
213.	feature	P_UTD331	0.02%	
214.	feature	FLU5_AGE	0.02%	
215.	feature	P_UTDHIB_SHORT_S		0.02%
216.	feature	DPCV5	0.02%	
217.	feature	XMMRTY2	0.02%	
218.	feature	P_UTDPCVB13	0.02%	
219.	feature	XHIBTY3	0.02%	
220.	feature	XHIBTY4	0.02%	
221.	feature	P_UTDPC3	0.02%	
222.	feature	P_NUMOPV	0.02%	
223.	feature	DHEPB5	0.01%	
224.	feature	XDTPTY5	0.01%	
225.	feature	XPCVTY5	0.01%	
226.	feature	P_NUMMCN	0.01%	
227.	feature	P_NUMVRN	0.01%	
228.	feature	POL5_AGE	0.01%	
229.	feature	P_NUHPHB	0.01%	
230.	feature	DPOLIO5	0.01%	
231.	feature	DHEPA3	0.01%	
232.	feature	P_UTDTP3	0.01%	
233.	feature	P_NUMPCP	0.01%	
234.	feature	HEA3_AGE	0.01%	
235.	feature	HEP5_AGE	0.01%	

236.	feature	XHEPTY5	0.01%
237.	feature	XHIBTY1	0.01%
238.	feature	P_NUMMPR	0.01%
239.	feature	P_NUMPCCN	0.01%
240.	feature	P_NUMMS	0.01%
241.	feature	PDAT	0.01%
242.	feature	P_NUMMSM	0.01%
243.	feature	XHIBTY2	0.00%
244.	feature	P_NUMMSR	0.00%
245.	feature	P_NUMMP	0.00%
246.	feature	P_NUMRB	0.00%
247.	feature	XPOLTY5	0.00%
248.	feature	ROT4_AGE	0.00%
249.	feature	HEP_FLAG	0.00%
250.	feature	DR0T4	0.00%
251.	feature	DPCV6	0.00%
252.	feature	DPOLIO6	0.00%
253.	feature	XPOLTY6	0.00%
254.	feature	XPCVTY6	0.00%
255.	feature	HIB6_AGE	0.00%
256.	feature	DHEPB6	0.00%
257.	feature	DDTP6	0.00%
258.	feature	DTP6_AGE	0.00%
259.	feature	DHIB6	0.00%
260.	feature	PCV6_AGE	0.00%
261.	feature	XDTPTY6	0.00%
262.	feature	MMR3_AGE	0.00%
263.	feature	XHEPTY6	0.00%
264.	feature	DHEPA4	0.00%
265.	feature	DFLU6	0.00%
266.	feature	DHEPA5	0.00%
267.	feature	DHEPB8	0.00%
268.	feature	DDTP7	0.00%
269.	feature	DDTP8	0.00%
270.	feature	YEAR	0.00%
271.	feature	SHOTCARD	0.00%
272.	feature	BFENDFL06	0.00%
273.	feature	BFFORMFL06	0.00%
274.	feature	DHEPB9	0.00%
275.	feature	DDTP9	0.00%
276.	feature	DHEPB7	0.00%
277.	feature	DHEPA6	0.00%
278.	feature	DFLU7	0.00%
279.	feature	DFLU8	0.00%
280.	feature	DHEPA9	0.00%
281.	feature	DHEPA8	0.00%
282.	feature	DHEPA7	0.00%
283.	feature	DFLU9	0.00%
284.	feature	DRB1	0.00%
285.	feature	DHIB7	0.00%
286.	feature	MPR2_AGE	0.00%
287.	feature	ROT5_AGE	0.00%
288.	feature	ROT6_AGE	0.00%
289.	feature	ROT7_AGE	0.00%
290.	feature	ROT8_AGE	0.00%
291.	feature	ROT9_AGE	0.00%
292.	feature	VRC3_AGE	0.00%
293.	feature	VRC4_AGE	0.00%
294.	feature	VRC5_AGE	0.00%

295.	feature	VRC6_AGE	0.00%
296.	feature	VRC7_AGE	0.00%
297.	feature	VRC8_AGE	0.00%
298.	feature	VRC9_AGE	0.00%
299.	feature	XDTPTY7	0.00%
300.	feature	XDTPTY8	0.00%
301.	feature	XDTPTY9	0.00%
302.	feature	XFLUTY1	0.00%
303.	feature	XFLUTY2	0.00%
304.	feature	XFLUTY3	0.00%
305.	feature	XFLUTY4	0.00%
306.	feature	RB9_AGE	0.00%
307.	feature	RB8_AGE	0.00%
308.	feature	RB7_AGE	0.00%
309.	feature	PCV9_AGE	0.00%
310.	feature	MPR4_AGE	0.00%
311.	feature	MPR5_AGE	0.00%
312.	feature	MPR6_AGE	0.00%
313.	feature	MPR7_AGE	0.00%
314.	feature	MPR8_AGE	0.00%
315.	feature	MPR9_AGE	0.00%
316.	feature	PCV7_AGE	0.00%
317.	feature	PCV8_AGE	0.00%
318.	feature	POL6_AGE	0.00%
319.	feature	RB6_AGE	0.00%
320.	feature	POL7_AGE	0.00%
321.	feature	POL8_AGE	0.00%
322.	feature	POL9_AGE	0.00%
323.	feature	RB1_AGE	0.00%
324.	feature	RB2_AGE	0.00%
325.	feature	RB3_AGE	0.00%
326.	feature	RB4_AGE	0.00%
327.	feature	RB5_AGE	0.00%
328.	feature	XFLUTY5	0.00%
329.	feature	XFLUTY6	0.00%
330.	feature	XFLUTY7	0.00%
331.	feature	XROTTY9	0.00%
332.	feature	XROTTY1	0.00%
333.	feature	XROTTY2	0.00%
334.	feature	XROTTY3	0.00%
335.	feature	XROTTY4	0.00%
336.	feature	XROTTY5	0.00%
337.	feature	XROTTY6	0.00%
338.	feature	XROTTY7	0.00%
339.	feature	XROTTY8	0.00%
340.	feature	XVRCTY1	0.00%
341.	feature	XPOLTY8	0.00%
342.	feature	XVRCTY2	0.00%
343.	feature	XVRCTY3	0.00%
344.	feature	XVRCTY4	0.00%
345.	feature	XVRCTY5	0.00%
346.	feature	XVRCTY6	0.00%
347.	feature	XVRCTY7	0.00%
348.	feature	XVRCTY8	0.00%
349.	feature	XVRCTY9	0.00%
350.	feature	XPOLTY9	0.00%
351.	feature	XPOLTY7	0.00%
352.	feature	XFLUTY8	0.00%
353.	feature	XHIBTY9	0.00%

354.	feature	XFLUTY9	0.00%
355.	feature	XHEPTY7	0.00%
356.	feature	XHEPTY8	0.00%
357.	feature	XHEPTY9	0.00%
358.	feature	XHIBTY5	0.00%
359.	feature	XHIBTY6	0.00%
360.	feature	XHIBTY7	0.00%
361.	feature	XHIBTY8	0.00%
362.	feature	XMMRTY3	0.00%
363.	feature	XPCVTY9	0.00%
364.	feature	XMMRTY4	0.00%
365.	feature	XMMRTY5	0.00%
366.	feature	XMMRTY6	0.00%
367.	feature	XMMRTY7	0.00%
368.	feature	XMMRTY8	0.00%
369.	feature	XMMRTY9	0.00%
370.	feature	XPCVTY7	0.00%
371.	feature	XPCVTY8	0.00%
372.	feature	MPR3_AGE	0.00%
373.	feature	MPR1_AGE	0.00%
374.	feature	DHIB8	0.00%
375.	feature	MP9_AGE	0.00%
376.	feature	DMPRB6	0.00%
377.	feature	DMPRB7	0.00%
378.	feature	DMPRB8	0.00%
379.	feature	DMPRB9	0.00%
380.	feature	DPCV7	0.00%
381.	feature	DPCV8	0.00%
382.	feature	DPCV9	0.00%
383.	feature	DPOLIO7	0.00%
384.	feature	DPOLIO8	0.00%
385.	feature	DPOLIO9	0.00%
386.	feature	DRB2	0.00%
387.	feature	DRB4	0.00%
388.	feature	DRB5	0.00%
389.	feature	DRB6	0.00%
390.	feature	DRB7	0.00%
391.	feature	DRB8	0.00%
392.	feature	DRB9	0.00%
393.	feature	DROT5	0.00%
394.	feature	DROT6	0.00%
395.	feature	DMPRB5	0.00%
396.	feature	DMPRB4	0.00%
397.	feature	DMPRB3	0.00%
398.	feature	DMP1	0.00%
399.	feature	DHIB9	0.00%
400.	feature	DMMR3	0.00%
401.	feature	DMMR4	0.00%
402.	feature	DMMR5	0.00%
403.	feature	DMMR6	0.00%
404.	feature	DMMR7	0.00%
405.	feature	DMMR8	0.00%
406.	feature	DMMR9	0.00%
407.	feature	DMP2	0.00%
408.	feature	DMPRB2	0.00%
409.	feature	DMP3	0.00%
410.	feature	DMP4	0.00%
411.	feature	DMP5	0.00%
412.	feature	DMP6	0.00%

413.	feature	DMP7	0.00%
414.	feature	DMP8	0.00%
415.	feature	DMP9	0.00%
416.	feature	DMPRB1	0.00%
417.	feature	DROT7	0.00%
418.	feature	DROT8	0.00%
419.	feature	DROT9	0.00%
420.	feature	MMR8_AGE	0.00%
421.	feature	HEP9_AGE	0.00%
422.	feature	HIB7_AGE	0.00%
423.	feature	HIB8_AGE	0.00%
424.	feature	HIB9_AGE	0.00%
425.	feature	MMR4_AGE	0.00%
426.	feature	MMR5_AGE	0.00%
427.	feature	MMR6_AGE	0.00%
428.	feature	MMR7_AGE	0.00%
429.	feature	MMR9_AGE	0.00%
430.	feature	HEP7_AGE	0.00%
431.	feature	MP1_AGE	0.00%
432.	feature	MP2_AGE	0.00%
433.	feature	MP3_AGE	0.00%
434.	feature	MP4_AGE	0.00%
435.	feature	MP5_AGE	0.00%
436.	feature	MP6_AGE	0.00%
437.	feature	MP7_AGE	0.00%
438.	feature	MP8_AGE	0.00%
439.	feature	HEP8_AGE	0.00%
440.	feature	HEP6_AGE	0.00%
441.	feature	DVRC3	0.00%
442.	feature	DTP9_AGE	0.00%
443.	feature	DVRC4	0.00%
444.	feature	DVRC5	0.00%
445.	feature	DVRC6	0.00%
446.	feature	DVRC7	0.00%
447.	feature	DVRC8	0.00%
448.	feature	DVRC9	0.00%
449.	feature	DTP7_AGE	0.00%
450.	feature	DTP8_AGE	0.00%
451.	feature	FLU6_AGE	0.00%
452.	feature	HEA9_AGE	0.00%
453.	feature	FLU7_AGE	0.00%
454.	feature	FLU8_AGE	0.00%
455.	feature	FLU9_AGE	0.00%
456.	feature	HEA4_AGE	0.00%
457.	feature	HEA5_AGE	0.00%
458.	feature	HEA6_AGE	0.00%
459.	feature	HEA7_AGE	0.00%
460.	feature	HEA8_AGE	0.00%
461.	feature	DRB3	0.00%

Hmmm... Our random number turns out to be the third most important feature for my target variable of FRSTBRN.

So my FRSTBRN investigation shows the top 2 variables for determining whether a child is firstborn are:

- \* CHILDNM -- Number of children in the household, and
- \* C1R -- Number of people in the household.

That's kinda sad!

Lesson of the day, choose your variables wisely.

## Assignment Requirements

Now it's your turn to perform a similar type of analysis.

Using the immunization dataset, complete the following:

1) Load the dataset and cleanup the missing values.

- As noted above, you need to do more than I did in my demonstration.
- Defend your handling of these values.
  - Tell me why are you doing what you are doing to the data, it matters! 2) Choose your own target variable (can be categorical or continuous, if you feel brave) 3) Determine if any of the variables are correlated to each other.
- Produce a correlation matrix at a minimum.
- If you decide to do a pairplot, remember the warning about wide datasets.
- Use the Random Number Trick to determine relevant variables.
  - Remember to check the accuracy of your model, before making any decisions.
    - If your accuracy is under 85%, you should improve your model or select a new target variable.
  - 4) Reduce the dataset to only include correlated variables from above.
  - 5) Complete EDA using the lecture notebook as a baseline -- feel free to add your own tests.
    - Produce visualizations for each of your remaining columns.
    - Explain what your visuals are telling you about your data. Be specific!
  - 6) Based on EDA results, either
    - Go back for more variables, or
    - Drop more variables
  - 7) Summary/conclude of your findings. Be specific and detailed in your explanations.
    - What do all the visuals mean in your analysis?
    - Why did you handle the data the way you did?
    - Don't assume I'll understand based on your code.



# Deliverables

## 1) Load the dataset and cleanup the missing values.

- As noted above, you need to do more than I did in my demonstration.
- Defend your handling of these values.
  - Tell me why are you doing what you are doing to the data, it matters!

```
In [32]: # Loading the dataset
df = pd.read_csv("assign_wk5/nispu14.csv", na_values=['.'], low_memory=False)
```

```
In [33]: # Taking a Look at the dataset
df.head()
```

```
Out[33]:
```

	SEQNUMC	SEQNUMHH	PDAT	PROVWT_D	PROVWT_D_TERR	RDDWT_D	F
0	11	1	2	.	.	218.30024855484000	
1	21	2	1	806.84601169505000	806.84601169505000	454.86041741251200	
2	31	3	2	.	.	30.54542540283290	
3	41	4	1	63.44868567610260	63.44868567610260	36.96593137368630	
4	51	5	1	94.87263225744540	94.87263225744540	64.62020426239790	

5 rows × 461 columns

As was demonstrated above, a lot of things, like age, are being stored in object form. I am going to go ahead and change these to numbers.

```
In [34]: for col in df.columns:
df[col] = pd.to_numeric(df[col], errors='coerce')
```

```
In [35]: # Making a copy of the data frame
df_new = df
```

After looking at a lot of the data, and trying other methods, filling the continuous values with the mean is probably the lesser of all the evils. A lot of the missing data is things like weight of child, and there is just not a good way to impute it any other way. There are 122 continuous variables, if you had all the time in the world you could come up with an individual solution for each, like imputing weight based on the average of that age category. This may give you a cleaner result.

One thing that I did notice is that the number of values missing in a lot of the rows is the same. After reading through the report I found the following:



To start, I want to limit the rows to only those that have "Adequate Provider Data" I am going to do that using the code below.

```
In [36]: # Picked a random column that has 15,059 from the vaccine info.  
df_adequate = df.dropna(subset=['P_NUHEPX'])
```

```
In [ ]: df_adequate.info(verbose=True, show_counts=True)
```

It is going to be helpful to separate the values into catagorical values AND continous values. As such I am going to use the code that was shown above to kick off dealing with the missing values.

```
In [38]: # Using the code from the example to split the data into continous and categorical

from itertools import tee, islice, chain

def previous_and_next(some_iterable):
    prevs, items, nexts = tee(some_iterable, 3)
    prevs = chain([None], prevs)
    nexts = chain(islice(nexts, 1, None), [None])
    return zip(prevs, items, nexts)

cont_list = []
for prev, item, nxt in previous_and_next(outlines):
    if isinstance(item, list):
        if 'Continuous' in str(item[0].title):
            cont_list.append(prev.title)

cont_list[:5]

cat_list = [c for c in df_adequate.columns if c not in cont_list]
```

Catagorical values are going to get a 0, that way I can later use the column as a catagory and just know that 0 means "Unknown" or missing.

```
In [ ]: for col in cat_list:
        df_adequate[col].fillna(0, inplace=True)
```

```
In [40]: df_adequate.info(verbose=True, show_counts=True)
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
Index: 15059 entries, 1 to 24896
```

```
Data columns (total 461 columns):
```

#	Column	Non-Null Count	Dtype
0	SEQNUMC	15059 non-null	int64
1	SEQNUMHH	15059 non-null	int64
2	PDAT	15059 non-null	int64
3	PROVWT_D	14893 non-null	float64
4	PROVWT_D_TERR	15059 non-null	float64
5	RDDWT_D	14893 non-null	float64
6	RDDWT_D_TERR	15059 non-null	float64
7	STRATUM	15059 non-null	int64
8	YEAR	15059 non-null	int64
9	AGECPOXR	15059 non-null	float64
10	HAD_CPOX	15059 non-null	int64
11	SHOTCARD	15059 non-null	int64
12	AGEGRP	15059 non-null	int64
13	BF_ENDR06	11724 non-null	float64
14	BF_EXCLR06	12100 non-null	float64
15	BF_FORMR08	10516 non-null	float64
16	BFENDFL06	15059 non-null	float64
17	BFFORMFL06	15059 non-null	float64
18	C1R	15059 non-null	int64
19	C5R	15059 non-null	int64
20	CBF_01	15059 non-null	int64
21	CEN_REG	15059 non-null	float64
22	CHILDNM	15059 non-null	int64
23	CWIC_01	15059 non-null	int64
24	CWIC_02	15059 non-null	float64
25	EDUC1	15059 non-null	int64
26	FRSTBRN	15059 non-null	int64
27	I_HISP_K	15059 non-null	int64
28	INCPORAR	14218 non-null	float64
29	INCPOV1	15059 non-null	int64
30	INCQ298A	15059 non-null	int64
31	INTRP	15059 non-null	float64
32	LANGUAGE	15059 non-null	int64
33	M_AGEGRP	15059 non-null	int64
34	MARITAL2	15059 non-null	int64
35	MOBIL_I	15059 non-null	int64
36	NUM_PHONE	15059 non-null	float64
37	NUM_CELLS_HH	15059 non-null	float64
38	NUM_CELLS_PARENTS	15059 non-null	float64
39	RACE_K	15059 non-null	int64
40	RACEETHK	15059 non-null	int64
41	RENT_OWN	15059 non-null	int64
42	SEX	15059 non-null	int64
43	ESTIAP14	15059 non-null	int64
44	EST_GRANT	15059 non-null	float64
45	STATE	15059 non-null	int64
46	D6R	15059 non-null	float64
47	D7	15059 non-null	float64
48	N_PRVR	15059 non-null	int64
49	PROV_FAC	15059 non-null	float64
50	REGISTRY	15059 non-null	float64
51	VFC_ORDER	15059 non-null	float64
52	HEP_BRTH	15059 non-null	float64
53	HEP_FLAG	15059 non-null	float64

54	P_NUHEPX	15059	non-null	float64
55	P_NUHIBX	15059	non-null	float64
56	P_NUHPHB	15059	non-null	float64
57	P_NUMDAH	15059	non-null	float64
58	P_NUMDHI	15059	non-null	float64
59	P_NUMDIH	15059	non-null	float64
60	P_NUMDTA	15059	non-null	float64
61	P_NUMDTP	15059	non-null	float64
62	P_NUMFLU	15059	non-null	float64
63	P_NUMFLUL	15059	non-null	float64
64	P_NUMFLUM	15059	non-null	float64
65	P_NUMFLUN	15059	non-null	float64
66	P_NUMHEA	15059	non-null	float64
67	P_NUMHEN	15059	non-null	float64
68	P_NUMHEP	15059	non-null	float64
69	P_NUMHG	15059	non-null	float64
70	P_NUMHHY	15059	non-null	float64
71	P_NUMHIB	15059	non-null	float64
72	P_NUMHIN	15059	non-null	float64
73	P_NUMHION	15059	non-null	float64
74	P_NUMHM	15059	non-null	float64
75	P_NUMHS	15059	non-null	float64
76	P_NUMIPV	15059	non-null	float64
77	P_NUMMCN	15059	non-null	float64
78	P_NUMMMR	15059	non-null	float64
79	P_NUMMMRX	15059	non-null	float64
80	P_NUMMMX	15059	non-null	float64
81	P_NUMMP	15059	non-null	float64
82	P_NUMMPR	15059	non-null	float64
83	P_NUMMRV	15059	non-null	float64
84	P_NUMMS	15059	non-null	float64
85	P_NUMMSM	15059	non-null	float64
86	P_NUMMSR	15059	non-null	float64
87	P_NUMOLN	15059	non-null	float64
88	P_NUMOPV	15059	non-null	float64
89	P_NUMPCV	15059	non-null	float64
90	P_NUMPCP	15059	non-null	float64
91	P_NUMPCC	15059	non-null	float64
92	P_NUMPCC7	15059	non-null	float64
93	P_NUMPCC13	15059	non-null	float64
94	P_NUMPCCN	15059	non-null	float64
95	P_NUMPCN	15059	non-null	float64
96	P_NUMPOL	15059	non-null	float64
97	P_NUMRB	15059	non-null	float64
98	P_NUMRG	15059	non-null	float64
99	P_NUMRM	15059	non-null	float64
100	P_NUMRO	15059	non-null	float64
101	P_NUMROT	15059	non-null	float64
102	P_NUMTPN	15059	non-null	float64
103	P_NUMVRC	15059	non-null	float64
104	P_NUMVRN	15059	non-null	float64
105	P_NUMVRX	15059	non-null	float64
106	P_U12VRC	15059	non-null	float64
107	P_UTD331	15059	non-null	float64
108	P_UTD431	15059	non-null	float64
109	P_UTDHEP	15059	non-null	float64
110	P_UTDHEPA1	15059	non-null	float64
111	P_UTDHEPA2	15059	non-null	float64
112	P_UTDHIB	15059	non-null	float64

113	P_UTDHIB_ROUT_S	15059	non-null	float64
114	P_UTDHIB_SHORT_S	15059	non-null	float64
115	P_UTDMCV	15059	non-null	float64
116	P_UTDMMX	15059	non-null	float64
117	P_UTDPC3	15059	non-null	float64
118	P_UTDPCV	15059	non-null	float64
119	P_UTDPCVB13	15059	non-null	float64
120	P_UTDPOL	15059	non-null	float64
121	P_UTDROT_S	15059	non-null	float64
122	P_UTDTP3	15059	non-null	float64
123	P_UTDTP4	15059	non-null	float64
124	PU431331	15059	non-null	float64
125	P_UTD431H31_ROUT_S	15059	non-null	float64
126	PU431_31	15059	non-null	float64
127	PU4313313	15059	non-null	float64
128	P_UTD431H313_ROUT_S	15059	non-null	float64
129	PU4313314	15059	non-null	float64
130	P_UTD431H314_ROUT_S	15059	non-null	float64
131	PU431_314	15059	non-null	float64
132	PUT43133	15059	non-null	float64
133	P_UTD431H3_ROUT_S	15059	non-null	float64
134	PUTD4313	15059	non-null	float64
135	P_UTD431H_ROUT_S	15059	non-null	float64
136	U1D_HEP	15059	non-null	float64
137	U2D_HEP	15059	non-null	float64
138	U3D_HEP	15059	non-null	float64
139	DDTP1	14688	non-null	float64
140	DDTP2	14547	non-null	float64
141	DDTP3	14345	non-null	float64
142	DDTP4	13007	non-null	float64
143	DDTP5	216	non-null	float64
144	DDTP6	7	non-null	float64
145	DDTP7	15059	non-null	float64
146	DDTP8	15059	non-null	float64
147	DDTP9	15059	non-null	float64
148	DFLU1	11205	non-null	float64
149	DFLU2	9292	non-null	float64
150	DFLU3	6102	non-null	float64
151	DFLU4	1755	non-null	float64
152	DFLU5	103	non-null	float64
153	DFLU6	4	non-null	float64
154	DFLU7	15059	non-null	float64
155	DFLU8	15059	non-null	float64
156	DFLU9	15059	non-null	float64
157	DHEPA1	12910	non-null	float64
158	DHEPA2	9379	non-null	float64
159	DHEPA3	63	non-null	float64
160	DHEPA4	3	non-null	float64
161	DHEPA5	15059	non-null	float64
162	DHEPA6	15059	non-null	float64
163	DHEPA7	15059	non-null	float64
164	DHEPA8	15059	non-null	float64
165	DHEPA9	15059	non-null	float64
166	DHEPB1	14665	non-null	float64
167	DHEPB2	14334	non-null	float64
168	DHEPB3	13844	non-null	float64
169	DHEPB4	3869	non-null	float64
170	DHEPB5	154	non-null	float64
171	DHEPB6	9	non-null	float64

172	DHEPB7	1 non-null	float64
173	DHEPB8	15059 non-null	float64
174	DHEPB9	15059 non-null	float64
175	DHIB1	14625 non-null	float64
176	DHIB2	14436 non-null	float64
177	DHIB3	14079 non-null	float64
178	DHIB4	10905 non-null	float64
179	DHIB5	170 non-null	float64
180	DHIB6	6 non-null	float64
181	DHIB7	1 non-null	float64
182	DHIB8	15059 non-null	float64
183	DHIB9	15059 non-null	float64
184	DMMR1	14047 non-null	float64
185	DMMR2	285 non-null	float64
186	DMMR3	2 non-null	float64
187	DMMR4	1 non-null	float64
188	DMMR5	15059 non-null	float64
189	DMMR6	15059 non-null	float64
190	DMMR7	15059 non-null	float64
191	DMMR8	15059 non-null	float64
192	DMMR9	15059 non-null	float64
193	DMP1	15059 non-null	float64
194	DMP2	15059 non-null	float64
195	DMP3	15059 non-null	float64
196	DMP4	15059 non-null	float64
197	DMP5	15059 non-null	float64
198	DMP6	15059 non-null	float64
199	DMP7	15059 non-null	float64
200	DMP8	15059 non-null	float64
201	DMP9	15059 non-null	float64
202	DMPRB1	1 non-null	float64
203	DMPRB2	15059 non-null	float64
204	DMPRB3	15059 non-null	float64
205	DMPRB4	15059 non-null	float64
206	DMPRB5	15059 non-null	float64
207	DMPRB6	15059 non-null	float64
208	DMPRB7	15059 non-null	float64
209	DMPRB8	15059 non-null	float64
210	DMPRB9	15059 non-null	float64
211	DPCV1	14578 non-null	float64
212	DPCV2	14381 non-null	float64
213	DPCV3	14091 non-null	float64
214	DPCV4	12862 non-null	float64
215	DPCV5	194 non-null	float64
216	DPCV6	6 non-null	float64
217	DPCV7	1 non-null	float64
218	DPCV8	15059 non-null	float64
219	DPCV9	15059 non-null	float64
220	DPOLIO1	14602 non-null	float64
221	DPOLIO2	14463 non-null	float64
222	DPOLIO3	14135 non-null	float64
223	DPOLIO4	2122 non-null	float64
224	DPOLIO5	58 non-null	float64
225	DPOLIO6	5 non-null	float64
226	DPOLIO7	15059 non-null	float64
227	DPOLIO8	15059 non-null	float64
228	DPOLIO9	15059 non-null	float64
229	DRB1	1 non-null	float64
230	DRB2	15059 non-null	float64

231	DRB3	15059	non-null	float64
232	DRB4	15059	non-null	float64
233	DRB5	15059	non-null	float64
234	DRB6	15059	non-null	float64
235	DRB7	15059	non-null	float64
236	DRB8	15059	non-null	float64
237	DRB9	15059	non-null	float64
238	DROT1	13141	non-null	float64
239	DROT2	12617	non-null	float64
240	DROT3	8643	non-null	float64
241	DROT4	21	non-null	float64
242	DROT5	1	non-null	float64
243	DROT6	15059	non-null	float64
244	DROT7	15059	non-null	float64
245	DROT8	15059	non-null	float64
246	DROT9	15059	non-null	float64
247	DVRC1	13886	non-null	float64
248	DVRC2	243	non-null	float64
249	DVRC3	2	non-null	float64
250	DVRC4	15059	non-null	float64
251	DVRC5	15059	non-null	float64
252	DVRC6	15059	non-null	float64
253	DVRC7	15059	non-null	float64
254	DVRC8	15059	non-null	float64
255	DVRC9	15059	non-null	float64
256	DTP1_AGE	14688	non-null	float64
257	DTP2_AGE	14547	non-null	float64
258	DTP3_AGE	14345	non-null	float64
259	DTP4_AGE	13007	non-null	float64
260	DTP5_AGE	216	non-null	float64
261	DTP6_AGE	7	non-null	float64
262	DTP7_AGE	15059	non-null	float64
263	DTP8_AGE	15059	non-null	float64
264	DTP9_AGE	15059	non-null	float64
265	FLU1_AGE	11205	non-null	float64
266	FLU2_AGE	9292	non-null	float64
267	FLU3_AGE	6102	non-null	float64
268	FLU4_AGE	1755	non-null	float64
269	FLU5_AGE	103	non-null	float64
270	FLU6_AGE	4	non-null	float64
271	FLU7_AGE	15059	non-null	float64
272	FLU8_AGE	15059	non-null	float64
273	FLU9_AGE	15059	non-null	float64
274	HEA1_AGE	12910	non-null	float64
275	HEA2_AGE	9379	non-null	float64
276	HEA3_AGE	63	non-null	float64
277	HEA4_AGE	3	non-null	float64
278	HEA5_AGE	15059	non-null	float64
279	HEA6_AGE	15059	non-null	float64
280	HEA7_AGE	15059	non-null	float64
281	HEA8_AGE	15059	non-null	float64
282	HEA9_AGE	15059	non-null	float64
283	HEP1_AGE	14665	non-null	float64
284	HEP2_AGE	14334	non-null	float64
285	HEP3_AGE	13844	non-null	float64
286	HEP4_AGE	3869	non-null	float64
287	HEP5_AGE	154	non-null	float64
288	HEP6_AGE	9	non-null	float64
289	HEP7_AGE	1	non-null	float64



290	HEP8_AGE	15059	non-null	float64
291	HEP9_AGE	15059	non-null	float64
292	HIB1_AGE	14625	non-null	float64
293	HIB2_AGE	14436	non-null	float64
294	HIB3_AGE	14079	non-null	float64
295	HIB4_AGE	10905	non-null	float64
296	HIB5_AGE	170	non-null	float64
297	HIB6_AGE	6	non-null	float64
298	HIB7_AGE	1	non-null	float64
299	HIB8_AGE	15059	non-null	float64
300	HIB9_AGE	15059	non-null	float64
301	MMR1_AGE	14047	non-null	float64
302	MMR2_AGE	285	non-null	float64
303	MMR3_AGE	2	non-null	float64
304	MMR4_AGE	1	non-null	float64
305	MMR5_AGE	15059	non-null	float64
306	MMR6_AGE	15059	non-null	float64
307	MMR7_AGE	15059	non-null	float64
308	MMR8_AGE	15059	non-null	float64
309	MMR9_AGE	15059	non-null	float64
310	MP1_AGE	15059	non-null	float64
311	MP2_AGE	15059	non-null	float64
312	MP3_AGE	15059	non-null	float64
313	MP4_AGE	15059	non-null	float64
314	MP5_AGE	15059	non-null	float64
315	MP6_AGE	15059	non-null	float64
316	MP7_AGE	15059	non-null	float64
317	MP8_AGE	15059	non-null	float64
318	MP9_AGE	15059	non-null	float64
319	MPR1_AGE	1	non-null	float64
320	MPR2_AGE	15059	non-null	float64
321	MPR3_AGE	15059	non-null	float64
322	MPR4_AGE	15059	non-null	float64
323	MPR5_AGE	15059	non-null	float64
324	MPR6_AGE	15059	non-null	float64
325	MPR7_AGE	15059	non-null	float64
326	MPR8_AGE	15059	non-null	float64
327	MPR9_AGE	15059	non-null	float64
328	PCV1_AGE	14578	non-null	float64
329	PCV2_AGE	14381	non-null	float64
330	PCV3_AGE	14091	non-null	float64
331	PCV4_AGE	12862	non-null	float64
332	PCV5_AGE	194	non-null	float64
333	PCV6_AGE	6	non-null	float64
334	PCV7_AGE	1	non-null	float64
335	PCV8_AGE	15059	non-null	float64
336	PCV9_AGE	15059	non-null	float64
337	POL1_AGE	14602	non-null	float64
338	POL2_AGE	14463	non-null	float64
339	POL3_AGE	14135	non-null	float64
340	POL4_AGE	2122	non-null	float64
341	POL5_AGE	58	non-null	float64
342	POL6_AGE	5	non-null	float64
343	POL7_AGE	15059	non-null	float64
344	POL8_AGE	15059	non-null	float64
345	POL9_AGE	15059	non-null	float64
346	RB1_AGE	1	non-null	float64
347	RB2_AGE	15059	non-null	float64
348	RB3_AGE	15059	non-null	float64

349	RB4_AGE	15059	non-null	float64
350	RB5_AGE	15059	non-null	float64
351	RB6_AGE	15059	non-null	float64
352	RB7_AGE	15059	non-null	float64
353	RB8_AGE	15059	non-null	float64
354	RB9_AGE	15059	non-null	float64
355	ROT1_AGE	13141	non-null	float64
356	ROT2_AGE	12617	non-null	float64
357	ROT3_AGE	8643	non-null	float64
358	ROT4_AGE	21	non-null	float64
359	ROT5_AGE	1	non-null	float64
360	ROT6_AGE	15059	non-null	float64
361	ROT7_AGE	15059	non-null	float64
362	ROT8_AGE	15059	non-null	float64
363	ROT9_AGE	15059	non-null	float64
364	VRC1_AGE	13886	non-null	float64
365	VRC2_AGE	243	non-null	float64
366	VRC3_AGE	2	non-null	float64
367	VRC4_AGE	15059	non-null	float64
368	VRC5_AGE	15059	non-null	float64
369	VRC6_AGE	15059	non-null	float64
370	VRC7_AGE	15059	non-null	float64
371	VRC8_AGE	15059	non-null	float64
372	VRC9_AGE	15059	non-null	float64
373	XDTPTY1	15059	non-null	float64
374	XDTPTY2	15059	non-null	float64
375	XDTPTY3	15059	non-null	float64
376	XDTPTY4	15059	non-null	float64
377	XDTPTY5	15059	non-null	float64
378	XDTPTY6	15059	non-null	float64
379	XDTPTY7	15059	non-null	float64
380	XDTPTY8	15059	non-null	float64
381	XDTPTY9	15059	non-null	float64
382	XFLUTY1	15059	non-null	float64
383	XFLUTY2	15059	non-null	float64
384	XFLUTY3	15059	non-null	float64
385	XFLUTY4	15059	non-null	float64
386	XFLUTY5	15059	non-null	float64
387	XFLUTY6	15059	non-null	float64
388	XFLUTY7	15059	non-null	float64
389	XFLUTY8	15059	non-null	float64
390	XFLUTY9	15059	non-null	float64
391	XHEPTY1	15059	non-null	float64
392	XHEPTY2	15059	non-null	float64
393	XHEPTY3	15059	non-null	float64
394	XHEPTY4	15059	non-null	float64
395	XHEPTY5	15059	non-null	float64
396	XHEPTY6	15059	non-null	float64
397	XHEPTY7	15059	non-null	float64
398	XHEPTY8	15059	non-null	float64
399	XHEPTY9	15059	non-null	float64
400	XHIBTY1	15059	non-null	float64
401	XHIBTY2	15059	non-null	float64
402	XHIBTY3	15059	non-null	float64
403	XHIBTY4	15059	non-null	float64
404	XHIBTY5	15059	non-null	float64
405	XHIBTY6	15059	non-null	float64
406	XHIBTY7	15059	non-null	float64
407	XHIBTY8	15059	non-null	float64

408	XHIBTY9	15059	non-null	float64
409	XMMRTY1	15059	non-null	float64
410	XMMRTY2	15059	non-null	float64
411	XMMRTY3	15059	non-null	float64
412	XMMRTY4	15059	non-null	float64
413	XMMRTY5	15059	non-null	float64
414	XMMRTY6	15059	non-null	float64
415	XMMRTY7	15059	non-null	float64
416	XMMRTY8	15059	non-null	float64
417	XMMRTY9	15059	non-null	float64
418	XPCVTY1	15059	non-null	float64
419	XPCVTY2	15059	non-null	float64
420	XPCVTY3	15059	non-null	float64
421	XPCVTY4	15059	non-null	float64
422	XPCVTY5	15059	non-null	float64
423	XPCVTY6	15059	non-null	float64
424	XPCVTY7	15059	non-null	float64
425	XPCVTY8	15059	non-null	float64
426	XPCVTY9	15059	non-null	float64
427	XPOLTY1	15059	non-null	float64
428	XPOLTY2	15059	non-null	float64
429	XPOLTY3	15059	non-null	float64
430	XPOLTY4	15059	non-null	float64
431	XPOLTY5	15059	non-null	float64
432	XPOLTY6	15059	non-null	float64
433	XPOLTY7	15059	non-null	float64
434	XPOLTY8	15059	non-null	float64
435	XPOLTY9	15059	non-null	float64
436	XROTTY1	15059	non-null	float64
437	XROTTY2	15059	non-null	float64
438	XROTTY3	15059	non-null	float64
439	XROTTY4	15059	non-null	float64
440	XROTTY5	15059	non-null	float64
441	XROTTY6	15059	non-null	float64
442	XROTTY7	15059	non-null	float64
443	XROTTY8	15059	non-null	float64
444	XROTTY9	15059	non-null	float64
445	XVRCTY1	15059	non-null	float64
446	XVRCTY2	15059	non-null	float64
447	XVRCTY3	15059	non-null	float64
448	XVRCTY4	15059	non-null	float64
449	XVRCTY5	15059	non-null	float64
450	XVRCTY6	15059	non-null	float64
451	XVRCTY7	15059	non-null	float64
452	XVRCTY8	15059	non-null	float64
453	XVRCTY9	15059	non-null	float64
454	INS_1	15059	non-null	float64
455	INS_2	15059	non-null	float64
456	INS_3	15059	non-null	float64
457	INS_3A	15059	non-null	float64
458	INS_4_5	15059	non-null	float64
459	INS_6	15059	non-null	float64
460	INS_11	15059	non-null	float64

dtypes: float64(432), int64(29)

memory usage: 53.1 MB

## Making some progress!! Columns that still have missing information:

- 3 this is child weight
- 5 this is child weight, but from a different source and time
- 13,14,15 are information on breastfeeding, going to be impossible to fill this with anything other than "unknown"
- 18 this is census region, some if just missing, it could be imputed from other geographic data
- 26 this is income to poverty ratio
- 34 the number of landlines in the home, more than 50% of that data it missing

It is going to be impossible to fill in things like the child's breastfeeding habit, so this information either needs a dummy value or to be removed from the data set. Same with the child's weight. You can not impute it based on age, as kids vary so much in size. You could use a mean for those values, but that will be less than ideal as well. This is where cleaning up data is so much effort. I do not want to toss out any more data, I already am taking just the "Adequate" information from the data and have filled in a lot of the categorical information with "Unknown". At this point the lesser of evils is to fill in the continuous data with the mean of the column.

```
In [41]: # Looking at a column with a lot of missing continuous data
df_adequate['DFLU3']
```

```
Out[41]: 1          421.0
          3          553.0
          4         1099.0
          5           NaN
          6           NaN
          ...
        24889         NaN
        24890         NaN
        24891         756.0
        24895         NaN
        24896         NaN
        Name: DFLU3, Length: 15059, dtype: float64
```

```
In [42]: df_full = df_adequate.fillna(df_adequate.mean())
```

Checking to see if there are still any missing values

```
In [43]: df_full.isnull().values.any()
```

```
Out[43]: False
```

## 2) Choose your own target variable (can be categorical or continuous, if you feel brave)

I am curious to look at chicken pox infections, data is stored as either a 1 - child had chicken pox, a 2 - child never had chicken pox, or 77, unknown, or 99 missing.

```
In [44]: df_pox = df_full
```

```
In [45]: # Looking at the unique values in the "had chicken pox" column  
df_pox['HAD_CPOX'].unique()
```

```
Out[45]: array([ 2,  1, 77], dtype=int64)
```

According to the code book "77" means "Unknown" if child had chicken pox, those are going to need to be dropped for our classifier.

```
In [46]: df_pox = df_pox[df_pox.HAD_CPOX != 77]
```

```
In [47]: # Looking at the unique values in the "had chicken pox" column  
df_pox['HAD_CPOX'].unique()
```

```
Out[47]: array([2, 1], dtype=int64)
```

## 3) Determine if any of the variables are correlated to each other.

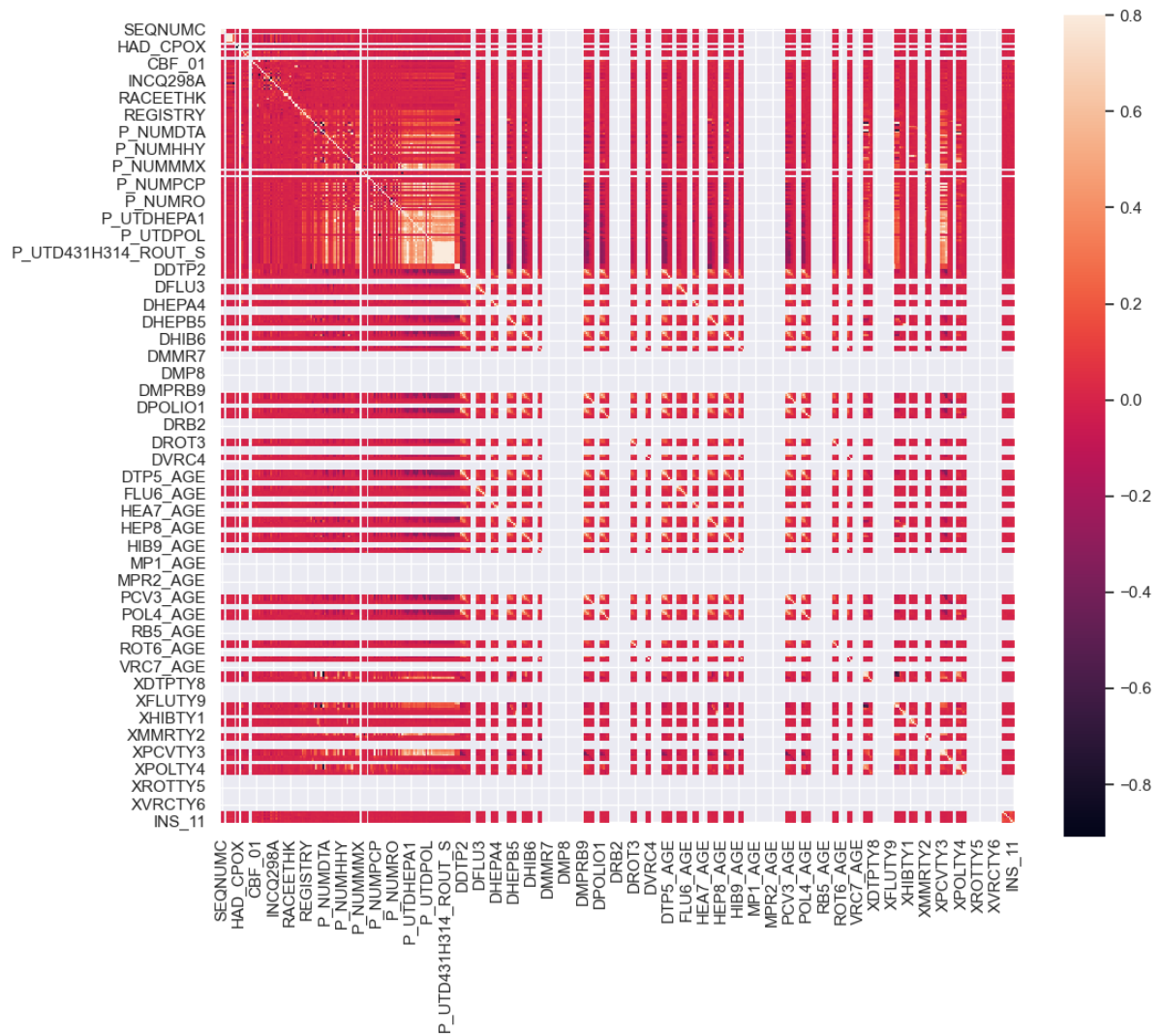
- Produce a correlation matrix at a minimum.
- If you decide to do a pairplot, remember the warning about wide datasets.
- Use the Random Number Trick to determine relevant variables.
  - Remember to check the accuracy of your model, before making any decisions.
    - If your accuracy is under 85%, you should improve your model or select a new target variable.

### Producing a correlation matrix

This is going to be a little bit of a challenge, considering there are 233 features. It is just going to be really large and hard to tell what is correlated or not. Below is a correlation matrix with all the data.

```
In [48]: corrmatrix = df_pox.corr()  
f, ax = plt.subplots(figsize=(12,10)) #setting some parameters of the plot to help  
sns.heatmap(corrmatrix, vmax = .8, square=True)
```

```
Out[48]: <Axes: >
```



It is going to be necessary to first pair down the features. This will be done following the method in the lecture material of creating a random number to use as a feature, and then selecting only features that perform better than the random number.

```
In [49]: from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier

y = df_pox.HAD_CPOX
x = df_pox.drop(['HAD_CPOX'], axis=1)
```

```
In [50]: # Creating the random number
np.random.seed(42)
x['random'] = np.random.normal(0.0, 1.0, size=x.shape[0])
```

C:\Users\matth\AppData\Local\Temp\ipykernel\_18632\1480610971.py:3: PerformanceWarning: DataFrame is highly fragmented. This is usually the result of calling `frame.insert` many times, which has poor performance. Consider joining all columns at once using `pd.concat(axis=1)` instead. To get a de-fragmented frame, use `newframe = frame.copy()`

```
x['random'] = np.random.normal(0.0, 1.0, size=x.shape[0])
```

```
In [51]: # Checking that the random number was added
x.head(10)
```

```
Out[51]:
```

	SEQNUMC	SEQNUMHH	PDAT	PROVWT_D	PROVWT_D_TERR	RDDWT_D	RDDWT_D_TERR	
1	21	2	1	806.846012	806.846012	454.860417	454.860417	
3	41	4	1	63.448686	63.448686	36.965931	36.965931	
4	51	5	1	94.872632	94.872632	64.620204	64.620204	
5	52	5	1	152.273845	152.273845	85.219413	85.219413	
6	61	6	1	210.186351	210.186351	112.170514	112.170514	
7	71	7	1	204.953336	204.953336	142.607339	142.607339	
8	81	8	1	1016.753531	1016.753531	499.775831	499.775831	
11	111	11	1	390.532585	390.532585	177.088881	177.088881	
12	121	12	1	248.745510	248.745510	171.865720	171.865720	
13	131	13	1	489.064864	489.064864	396.329703	396.329703	

10 rows × 461 columns

```
In [52]: # Creating a 70/30 train test split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)

clf=RandomForestClassifier(n_estimators=100)
clf.fit(x_train,y_train)
```

```
Out[52]: ▼ RandomForestClassifier
RandomForestClassifier()
```

```
In [53]: # Running the random forest
features = x_train.columns
importances = clf.feature_importances_
std = np.std([tree.feature_importances_ for tree in clf.estimators_],
              axis=0)
indices = np.argsort(importances)[::-1]

# Save the feature ranking to a list for later use
# and print it on the screen

feature_rank = []
print("Feature ranking:")

for f in range(x_train.shape[1]):
    feature = f"{f + 1}. feature {features[indices[f]]} \t{importances[indices[f]]}"
    if 'random' in features[indices[f]]:
        feature += " <=="
    print(feature)
    feature_rank.append([features[indices[f]], importances[indices[f]]])
```

## Feature ranking:

1. feature AGECP0XR	39.53%	
2. feature SEQNUMC	1.00%	
3. feature SEQNUMHH	0.98%	
4. feature random	0.97%	<==
5. feature STRATUM	0.93%	
6. feature BF_ENDR06	0.85%	
7. feature PROVWT_D	0.83%	
8. feature PROVWT_D_TERR		0.80%
9. feature EST_GRANT	0.78%	
10. feature DDTP4	0.78%	
11. feature RDDWT_D_TERR		0.76%
12. feature DFLU1	0.73%	
13. feature ESTIAP14	0.71%	
14. feature DDTP2	0.69%	
15. feature BF_FORMR08		0.69%
16. feature DHEPB2	0.67%	
17. feature DHIB1	0.65%	
18. feature DHEPA2	0.64%	
19. feature RDDWT_D	0.63%	
20. feature DPCV1	0.63%	
21. feature DVRC1	0.62%	
22. feature DPCV4	0.62%	
23. feature DPCV2	0.62%	
24. feature DDTP1	0.62%	
25. feature BF_EXCLR06		0.61%
26. feature DHIB3	0.61%	
27. feature STATE	0.60%	
28. feature DHIB2	0.60%	
29. feature NUM_CELLS_HH		0.60%
30. feature DPCV3	0.59%	
31. feature DDTP3	0.59%	
32. feature DPOLIO3	0.59%	
33. feature INCPORAR	0.57%	
34. feature DROT3	0.55%	
35. feature DPOLIO1	0.55%	
36. feature EDUC1	0.55%	
37. feature DMMR1	0.55%	
38. feature DHIB4	0.55%	
39. feature DTP4_AGE	0.54%	
40. feature DPOLIO2	0.54%	
41. feature DFLU2	0.52%	
42. feature INCQ298A	0.51%	
43. feature NUM_CELLS_PARENTS		0.51%
44. feature FLU1_AGE	0.50%	
45. feature DHEPB3	0.48%	
46. feature HEP2_AGE	0.47%	
47. feature DROT2	0.47%	
48. feature DHEPB1	0.46%	
49. feature DHEPA1	0.45%	
50. feature VRC1_AGE	0.45%	
51. feature C1R	0.44%	
52. feature HIB4_AGE	0.43%	
53. feature PCV4_AGE	0.43%	
54. feature HIB3_AGE	0.42%	
55. feature DFLU3	0.42%	
56. feature HEA1_AGE	0.40%	
57. feature PCV2_AGE	0.39%	
58. feature DROT1	0.39%	



59. feature D6R	0.38%	
60. feature INS_11	0.38%	
61. feature HEA2_AGE	0.38%	
62. feature C5R	0.37%	
63. feature FLU2_AGE	0.36%	
64. feature POL3_AGE	0.36%	
65. feature DTP3_AGE	0.36%	
66. feature MMR1_AGE	0.35%	
67. feature INCP0V1	0.35%	
68. feature PROV_FAC	0.35%	
69. feature INS_2	0.34%	
70. feature CHILDNM	0.34%	
71. feature HEP3_AGE	0.34%	
72. feature CEN_REG	0.33%	
73. feature DHEPB4	0.33%	
74. feature P_NUMVRC	0.31%	
75. feature CWIC_02	0.31%	
76. feature P_NUMFLUN		0.31%
77. feature P_NUMDIH	0.30%	
78. feature DTP2_AGE	0.29%	
79. feature HIB1_AGE	0.28%	
80. feature FLU3_AGE	0.28%	
81. feature P_NUMDHI	0.28%	
82. feature N_PRVR	0.27%	
83. feature P_NUMFLU	0.26%	
84. feature HIB2_AGE	0.26%	
85. feature INS_3A	0.26%	
86. feature MARITAL2	0.25%	
87. feature ROT3_AGE	0.25%	
88. feature PCV1_AGE	0.25%	
89. feature P_NUMHS	0.25%	
90. feature HEP1_AGE	0.25%	
91. feature POL2_AGE	0.24%	
92. feature AGEGRP	0.24%	
93. feature INS_1	0.23%	
94. feature P_NUMPCC13		0.23%
95. feature P_NUHIBX	0.23%	
96. feature FLU4_AGE	0.23%	
97. feature INS_3	0.23%	
98. feature RENT_OWN	0.23%	
99. feature P_NUHEPX	0.22%	
100. feature POL4_AGE		0.22%
101. feature P_NUMFLUM		0.22%
102. feature P_NUMHIB		0.22%
103. feature DPOLIO4	0.21%	
104. feature CBF_01	0.21%	
105. feature P_NUMHM	0.20%	
106. feature P_NUMDTA		0.20%
107. feature PCV3_AGE		0.20%
108. feature P_NUMHEA		0.20%
109. feature INS_6	0.20%	
110. feature SEX	0.20%	
111. feature DTP1_AGE		0.20%
112. feature P_NUMROT		0.20%
113. feature P_NUMHEP		0.20%
114. feature REGISTRY		0.19%
115. feature RACEETHK		0.19%
116. feature VRC2_AGE		0.19%
117. feature XPOLTY1	0.18%	

118.	feature	P_NUMVRX	0.18%	
119.	feature	NUM_PHONE	0.17%	
120.	feature	VFC_ORDER	0.17%	
121.	feature	DFLU4	0.17%	
122.	feature	ROT1_AGE	0.17%	
123.	feature	INTRP	0.17%	
124.	feature	P_U12VRC	0.16%	
125.	feature	P_NUMPOL	0.16%	
126.	feature	XDTPTY2	0.16%	
127.	feature	XPOLTY3	0.16%	
128.	feature	FRSTBRN	0.16%	
129.	feature	INS_4_5	0.16%	
130.	feature	XPOLTY2	0.16%	
131.	feature	RACE_K	0.16%	
132.	feature	XHEPTY2	0.15%	
133.	feature	ROT2_AGE	0.15%	
134.	feature	XHEPTY3	0.15%	
135.	feature	P_NUMPCV	0.15%	
136.	feature	P_NUMDTP	0.15%	
137.	feature	P_NUMMMRX	0.14%	
138.	feature	P_NUMIPV	0.14%	
139.	feature	POL1_AGE	0.13%	
140.	feature	XDTPTY3	0.13%	
141.	feature	M_AGEGRP	0.13%	
142.	feature	P_NUMPCC	0.13%	
143.	feature	DDTP5	0.13%	
144.	feature	HEP_BRTH	0.13%	
145.	feature	CWIC_01	0.13%	
146.	feature	DTP5_AGE	0.13%	
147.	feature	P_NUMHIN	0.13%	
148.	feature	XPCVTY4	0.12%	
149.	feature	HEP4_AGE	0.12%	
150.	feature	I_HISP_K	0.12%	
151.	feature	XHEPTY1	0.12%	
152.	feature	DVRC2	0.12%	
153.	feature	P_NUMHEN	0.12%	
154.	feature	LANGUAGE	0.11%	
155.	feature	XMMRTY1	0.11%	
156.	feature	P_UTDHEPA2	0.11%	
157.	feature	PU431331	0.11%	
158.	feature	P_NUMHG	0.11%	
159.	feature	MMR2_AGE	0.11%	
160.	feature	P_UTDTP4	0.11%	
161.	feature	P_NUMRG	0.10%	
162.	feature	P_NUMRM	0.10%	
163.	feature	U2D_HEP	0.10%	
164.	feature	P_UTDMCV	0.10%	
165.	feature	P_UTD431H_ROUT_S	0.10%	0.10%
166.	feature	DMMR2	0.10%	
167.	feature	XDTPTY1	0.10%	
168.	feature	HEP5_AGE	0.10%	
169.	feature	XHEPTY4	0.10%	
170.	feature	MOBIL_I	0.10%	
171.	feature	XPCVTY2	0.10%	
172.	feature	PUT43133	0.09%	
173.	feature	P_UTDPCVB13	0.09%	
174.	feature	P_NUMMRV	0.09%	
175.	feature	P_NUMMMX	0.09%	
176.	feature	P_NUMHION	0.09%	

177.	feature	P_NUMMMR	0.09%	
178.	feature	XHIBTY3	0.08%	
179.	feature	P_UTD431H31_ROUT_S		0.08%
180.	feature	XDTPTY4	0.08%	
181.	feature	P_NUMTPN	0.08%	
182.	feature	XPCVTY1	0.08%	
183.	feature	DPOLIO5	0.07%	
184.	feature	P_UTD431H3_ROUT_S		0.07%
185.	feature	P_NUMPCC7	0.07%	
186.	feature	XPOLTY4	0.07%	
187.	feature	P_UTDHIB_ROUT_S	0.07%	
188.	feature	U3D_HEP	0.07%	
189.	feature	P_UTD431H313_ROUT_S		0.07%
190.	feature	PU431_31	0.07%	
191.	feature	P_UTD331	0.07%	
192.	feature	P_NUMFLUL	0.07%	
193.	feature	P_UTDHEPA1	0.06%	
194.	feature	P_UTD431H314_ROUT_S		0.06%
195.	feature	FLU5_AGE	0.06%	
196.	feature	XHIBTY1	0.06%	
197.	feature	PU4313314	0.06%	
198.	feature	XHEPTY5	0.06%	
199.	feature	DHIB5	0.06%	
200.	feature	PUTD4313	0.06%	
201.	feature	PCV5_AGE	0.05%	
202.	feature	P_NUMPCN	0.05%	
203.	feature	P_UTD431	0.05%	
204.	feature	D7	0.05%	
205.	feature	U1D_HEP	0.05%	
206.	feature	HIB5_AGE		0.05%
207.	feature	DPCV5	0.05%	
208.	feature	P_UTDMMX		0.05%
209.	feature	DFLU6	0.04%	
210.	feature	P_NUMRO	0.04%	
211.	feature	PU4313313		0.04%
212.	feature	DFLU5	0.04%	
213.	feature	XPCVTY3	0.04%	
214.	feature	P_UTDHIB_SHORT_S		0.04%
215.	feature	PU431_314	0.04%	
216.	feature	P_UTDPOL	0.03%	
217.	feature	P_UTDROT_S	0.03%	
218.	feature	P_UTDPCV	0.03%	
219.	feature	DHEPA3	0.03%	
220.	feature	XHIBTY2	0.03%	
221.	feature	FLU6_AGE		0.03%
222.	feature	XMMRTY2	0.02%	
223.	feature	P_NUHPHB	0.02%	
224.	feature	P_UTDHEP	0.02%	
225.	feature	P_UTDHIB	0.02%	
226.	feature	P_NUMOLN	0.02%	
227.	feature	HEA3_AGE	0.02%	
228.	feature	POL5_AGE	0.01%	
229.	feature	XHIBTY4	0.01%	
230.	feature	XPOLTY5	0.01%	
231.	feature	P_NUMHHY	0.01%	
232.	feature	P_UTDPC3	0.01%	
233.	feature	DHEPB5	0.01%	
234.	feature	P_UTDTP3		0.00%
235.	feature	XPCVTY5	0.00%	

236.	feature	DHEPB6	0.00%
237.	feature	BFENDFL06	0.00%
238.	feature	BFFORMFL06	0.00%
239.	feature	P_NUMMP	0.00%
240.	feature	P_NUMMPR	0.00%
241.	feature	PDAT	0.00%
242.	feature	DHEPB7	0.00%
243.	feature	DHEPB8	0.00%
244.	feature	DHEPB9	0.00%
245.	feature	SHOTCARD	0.00%
246.	feature	P_NUMMCN	0.00%
247.	feature	YEAR	0.00%
248.	feature	DHEPA8	0.00%
249.	feature	DHIB6	0.00%
250.	feature	DHIB7	0.00%
251.	feature	DHIB8	0.00%
252.	feature	DHIB9	0.00%
253.	feature	DHEPA9	0.00%
254.	feature	P_NUMOPV	0.00%
255.	feature	DHEPA7	0.00%
256.	feature	DMMR3	0.00%
257.	feature	HEP_FLAG	0.00%
258.	feature	DDTP6	0.00%
259.	feature	DDTP7	0.00%
260.	feature	DDTP8	0.00%
261.	feature	P_NUMVRN	0.00%
262.	feature	DDTP9	0.00%
263.	feature	P_NUMRB	0.00%
264.	feature	P_NUMPCCN	0.00%
265.	feature	DFLU7	0.00%
266.	feature	DHEPA6	0.00%
267.	feature	DFLU8	0.00%
268.	feature	DFLU9	0.00%
269.	feature	P_NUMDAH	0.00%
270.	feature	P_NUMMSR	0.00%
271.	feature	DHEPA4	0.00%
272.	feature	DHEPA5	0.00%
273.	feature	P_NUMMSM	0.00%
274.	feature	P_NUMMS	0.00%
275.	feature	P_NUMPCP	0.00%
276.	feature	DRB1	0.00%
277.	feature	DMMR4	0.00%
278.	feature	VRC9_AGE	0.00%
279.	feature	ROT7_AGE	0.00%
280.	feature	ROT8_AGE	0.00%
281.	feature	ROT9_AGE	0.00%
282.	feature	VRC3_AGE	0.00%
283.	feature	VRC4_AGE	0.00%
284.	feature	VRC5_AGE	0.00%
285.	feature	VRC6_AGE	0.00%
286.	feature	VRC7_AGE	0.00%
287.	feature	VRC8_AGE	0.00%
288.	feature	XDTPTY5	0.00%
289.	feature	MPR5_AGE	0.00%
290.	feature	XDTPTY6	0.00%
291.	feature	XDTPTY7	0.00%
292.	feature	XDTPTY8	0.00%
293.	feature	XDTPTY9	0.00%
294.	feature	XFLUTY1	0.00%

295.	feature	XFLUTY2	0.00%
296.	feature	XFLUTY3	0.00%
297.	feature	XFLUTY4	0.00%
298.	feature	XFLUTY5	0.00%
299.	feature	ROT6_AGE	0.00%
300.	feature	ROT5_AGE	0.00%
301.	feature	ROT4_AGE	0.00%
302.	feature	RB9_AGE	0.00%
303.	feature	MPR7_AGE	0.00%
304.	feature	MPR8_AGE	0.00%
305.	feature	MPR9_AGE	0.00%
306.	feature	PCV6_AGE	0.00%
307.	feature	PCV7_AGE	0.00%
308.	feature	PCV8_AGE	0.00%
309.	feature	PCV9_AGE	0.00%
310.	feature	POL6_AGE	0.00%
311.	feature	POL7_AGE	0.00%
312.	feature	POL8_AGE	0.00%
313.	feature	POL9_AGE	0.00%
314.	feature	RB1_AGE	0.00%
315.	feature	RB2_AGE	0.00%
316.	feature	RB3_AGE	0.00%
317.	feature	RB4_AGE	0.00%
318.	feature	RB5_AGE	0.00%
319.	feature	RB6_AGE	0.00%
320.	feature	RB7_AGE	0.00%
321.	feature	RB8_AGE	0.00%
322.	feature	XFLUTY6	0.00%
323.	feature	XFLUTY7	0.00%
324.	feature	XFLUTY8	0.00%
325.	feature	XPOLTY7	0.00%
326.	feature	XPOLTY9	0.00%
327.	feature	XROTTY1	0.00%
328.	feature	XROTTY2	0.00%
329.	feature	XROTTY3	0.00%
330.	feature	XROTTY4	0.00%
331.	feature	XROTTY5	0.00%
332.	feature	XROTTY6	0.00%
333.	feature	XROTTY7	0.00%
334.	feature	XROTTY8	0.00%
335.	feature	XROTTY9	0.00%
336.	feature	XVRCTY1	0.00%
337.	feature	XVRCTY2	0.00%
338.	feature	XVRCTY3	0.00%
339.	feature	XVRCTY4	0.00%
340.	feature	XVRCTY5	0.00%
341.	feature	XVRCTY6	0.00%
342.	feature	XVRCTY7	0.00%
343.	feature	XVRCTY8	0.00%
344.	feature	XVRCTY9	0.00%
345.	feature	XPOLTY8	0.00%
346.	feature	XPOLTY6	0.00%
347.	feature	XFLUTY9	0.00%
348.	feature	XPCVTY9	0.00%
349.	feature	XHEPTY6	0.00%
350.	feature	XHEPTY7	0.00%
351.	feature	XHEPTY8	0.00%
352.	feature	XHEPTY9	0.00%
353.	feature	XHIBTY5	0.00%

354.	feature	XHIBTY6	0.00%	
355.	feature	XHIBTY7	0.00%	
356.	feature	XHIBTY8	0.00%	
357.	feature	XHIBTY9	0.00%	
358.	feature	XMMRTY3	0.00%	
359.	feature	XMMRTY4	0.00%	
360.	feature	XMMRTY5	0.00%	
361.	feature	XMMRTY6	0.00%	
362.	feature	XMMRTY7	0.00%	
363.	feature	XMMRTY8	0.00%	
364.	feature	XMMRTY9	0.00%	
365.	feature	XPCVTY6	0.00%	
366.	feature	XPCVTY7	0.00%	
367.	feature	XPCVTY8	0.00%	
368.	feature	MPR6_AGE		0.00%
369.	feature	MPR4_AGE		0.00%
370.	feature	DMMR5	0.00%	
371.	feature	DRB5	0.00%	
372.	feature	DPCV7	0.00%	
373.	feature	DPCV8	0.00%	
374.	feature	DPCV9	0.00%	
375.	feature	DPOLIO6	0.00%	
376.	feature	DPOLIO7	0.00%	
377.	feature	DPOLIO8	0.00%	
378.	feature	DPOLIO9	0.00%	
379.	feature	DRB2	0.00%	
380.	feature	DRB4	0.00%	
381.	feature	DRB6	0.00%	
382.	feature	MPR3_AGE		0.00%
383.	feature	DRB7	0.00%	
384.	feature	DRB8	0.00%	
385.	feature	DRB9	0.00%	
386.	feature	DROT4	0.00%	
387.	feature	DROT5	0.00%	
388.	feature	DROT6	0.00%	
389.	feature	DROT7	0.00%	
390.	feature	DROT8	0.00%	
391.	feature	DROT9	0.00%	
392.	feature	DPCV6	0.00%	
393.	feature	DMPRB9	0.00%	
394.	feature	DMPRB8	0.00%	
395.	feature	DMPRB7	0.00%	
396.	feature	DMMR6	0.00%	
397.	feature	DMMR7	0.00%	
398.	feature	DMMR8	0.00%	
399.	feature	DMMR9	0.00%	
400.	feature	DMP1	0.00%	
401.	feature	DMP2	0.00%	
402.	feature	DMP3	0.00%	
403.	feature	DMP4	0.00%	
404.	feature	DMP5	0.00%	
405.	feature	DMP6	0.00%	
406.	feature	DMP7	0.00%	
407.	feature	DMP8	0.00%	
408.	feature	DMP9	0.00%	
409.	feature	DMPRB1	0.00%	
410.	feature	DMPRB2	0.00%	
411.	feature	DMPRB3	0.00%	
412.	feature	DMPRB4	0.00%	

413.	feature	DMPRB5	0.00%
414.	feature	DMPRB6	0.00%
415.	feature	DVRC3	0.00%
416.	feature	DVRC4	0.00%
417.	feature	DVRC5	0.00%
418.	feature	HIB7_AGE	0.00%
419.	feature	HIB9_AGE	0.00%
420.	feature	MMR3_AGE	0.00%
421.	feature	MMR4_AGE	0.00%
422.	feature	MMR5_AGE	0.00%
423.	feature	MMR6_AGE	0.00%
424.	feature	MMR7_AGE	0.00%
425.	feature	MMR8_AGE	0.00%
426.	feature	MMR9_AGE	0.00%
427.	feature	MP1_AGE	0.00%
428.	feature	MP2_AGE	0.00%
429.	feature	MP3_AGE	0.00%
430.	feature	MP4_AGE	0.00%
431.	feature	MP5_AGE	0.00%
432.	feature	MP6_AGE	0.00%
433.	feature	MP7_AGE	0.00%
434.	feature	MP8_AGE	0.00%
435.	feature	MP9_AGE	0.00%
436.	feature	MPR1_AGE	0.00%
437.	feature	MPR2_AGE	0.00%
438.	feature	HIB8_AGE	0.00%
439.	feature	HIB6_AGE	0.00%
440.	feature	DVRC6	0.00%
441.	feature	HEP9_AGE	0.00%
442.	feature	DVRC7	0.00%
443.	feature	DVRC8	0.00%
444.	feature	DVRC9	0.00%
445.	feature	DTP6_AGE	0.00%
446.	feature	DTP7_AGE	0.00%
447.	feature	DTP8_AGE	0.00%
448.	feature	DTP9_AGE	0.00%
449.	feature	FLU7_AGE	0.00%
450.	feature	FLU8_AGE	0.00%
451.	feature	FLU9_AGE	0.00%
452.	feature	HEA4_AGE	0.00%
453.	feature	HEA5_AGE	0.00%
454.	feature	HEA6_AGE	0.00%
455.	feature	HEA7_AGE	0.00%
456.	feature	HEA8_AGE	0.00%
457.	feature	HEA9_AGE	0.00%
458.	feature	HEP6_AGE	0.00%
459.	feature	HEP7_AGE	0.00%
460.	feature	HEP8_AGE	0.00%
461.	feature	DRB3	0.00%

Yikes!!! That is not good, there is only a single feature, Age at which child had chicken pox, that is a better indicator of if a child has had chicken pox, then a random number. That is just not going to work well for building a model. Lets try another possibility, Rent or Owning a home.

```
In [54]: df_rentown = df_full
```

```
In [55]: # Unique values in Rent or Own  
df_rentown['RENT_OWN'].unique()
```

```
Out[55]: array([ 2,  1,  3, 99, 77], dtype=int64)
```

The values in Rent / Own are either: 1 own (or buying) , 2 renting, 3 (other arrangement 3% of the data), or missing / unknown. I am going to drop anything other than 1 or 2.

```
In [56]: df_rentown = df_rentown[df_rentown.RENT_OWN != 3]  
df_rentown = df_rentown[df_rentown.RENT_OWN != 77]  
df_rentown = df_rentown[df_rentown.RENT_OWN != 99]
```

```
In [57]: # Unique values in Rent or Own  
df_rentown['RENT_OWN'].unique()
```

```
Out[57]: array([2, 1], dtype=int64)
```

```
In [58]: from sklearn.model_selection import train_test_split  
from sklearn.ensemble import RandomForestClassifier  
  
y = df_rentown.RENT_OWN  
x = df_rentown.drop(['RENT_OWN'], axis=1)
```

```
In [59]: # Creating the random number  
np.random.seed(42)  
x['random'] = np.random.normal(0.0, 1.0, size=x.shape[0])
```

C:\Users\matth\AppData\Local\Temp\ipykernel\_18632\1480610971.py:3: PerformanceWarning: DataFrame is highly fragmented. This is usually the result of calling `frame.insert` many times, which has poor performance. Consider joining all columns at once using `pd.concat(axis=1)` instead. To get a de-fragmented frame, use `newframe = frame.copy()`

```
    x['random'] = np.random.normal(0.0, 1.0, size=x.shape[0])
```

```
In [60]: # Checking that the random number was added  
x.head(10)
```



```
Out[60]:
```

	SEQNUMC	SEQNUMHH	PDAT	PROVWT_D	PROVWT_D_TERR	RDDWT_D	RDDWT_D_TERR	!
<b>1</b>	21	2	1	806.846012	806.846012	454.860417	454.860417	
<b>3</b>	41	4	1	63.448686	63.448686	36.965931	36.965931	
<b>4</b>	51	5	1	94.872632	94.872632	64.620204	64.620204	
<b>5</b>	52	5	1	152.273845	152.273845	85.219413	85.219413	
<b>6</b>	61	6	1	210.186351	210.186351	112.170514	112.170514	
<b>7</b>	71	7	1	204.953336	204.953336	142.607339	142.607339	
<b>8</b>	81	8	1	1016.753531	1016.753531	499.775831	499.775831	
<b>11</b>	111	11	1	390.532585	390.532585	177.088881	177.088881	
<b>12</b>	121	12	1	248.745510	248.745510	171.865720	171.865720	
<b>13</b>	131	13	1	489.064864	489.064864	396.329703	396.329703	

10 rows × 461 columns

```
In [61]: # Creating a 70/30 train test split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)

clf=RandomForestClassifier(n_estimators=100)
clf.fit(x_train,y_train)
```

```
Out[61]: ▼ RandomForestClassifier
RandomForestClassifier()
```

```
In [62]: # Running the random forest
features = x_train.columns
importances = clf.feature_importances_
std = np.std([tree.feature_importances_ for tree in clf.estimators_],
              axis=0)
indices = np.argsort(importances)[::-1]

# Save the feature ranking to a list for later use
# and print it on the screen

feature_rank = []
print("Feature ranking:")

for f in range(x_train.shape[1]):
    feature = f"{f + 1}. feature {features[indices[f]]} \t{importances[indices[f]]}"
    if 'random' in features[indices[f]]:
        feature += " <=="
    print(feature)
    feature_rank.append([features[indices[f]], importances[indices[f]]])
```

## Feature ranking:

1. feature INCQ298A	3.91%	
2. feature INCPORAR	3.56%	
3. feature CWIC_02	2.87%	
4. feature CWIC_01	2.32%	
5. feature INS_1	2.04%	
6. feature INCPOV1	1.99%	
7. feature RDDWT_D	1.55%	
8. feature PROVWT_D_TERR		1.54%
9. feature INTRP	1.51%	
10. feature PROVWT_D	1.46%	
11. feature RDDWT_D_TERR		1.41%
12. feature STRATUM	1.40%	
13. feature EDUC1	1.37%	
14. feature SEQNUMC	1.22%	
15. feature random	1.21%	<==
16. feature MARITAL2	1.20%	
17. feature NUM_CELLS_HH		1.18%
18. feature SEQNUMHH	1.11%	
19. feature ESTIAP14	1.11%	
20. feature EST_GRANT		1.09%
21. feature STATE	1.04%	
22. feature DPCV3	1.02%	
23. feature DDTP4	0.97%	
24. feature DHIB3	0.97%	
25. feature DDTP3	0.96%	
26. feature DHEPB3	0.96%	
27. feature DPOLIO3	0.96%	
28. feature DMMR1	0.96%	
29. feature DPCV4	0.95%	
30. feature BF_ENDR06		0.95%
31. feature DVRC1	0.94%	
32. feature DHEPB2	0.92%	
33. feature DFLU1	0.92%	
34. feature DHEPA1	0.92%	
35. feature RACEETHK	0.90%	
36. feature DPCV2	0.88%	
37. feature DPCV1	0.87%	
38. feature DHIB4	0.87%	
39. feature DHIB2	0.87%	
40. feature DDTP2	0.85%	
41. feature MOBIL_I	0.85%	
42. feature NUM_CELLS_PARENTS		0.84%
43. feature DPOLIO2	0.84%	
44. feature C1R	0.83%	
45. feature DHEPA2	0.83%	
46. feature DDTP1	0.82%	
47. feature DROT2	0.81%	
48. feature DFLU2	0.81%	
49. feature DHIB1	0.79%	
50. feature DROT1	0.78%	
51. feature M_AGEGRP	0.78%	
52. feature INS_2	0.77%	
53. feature DPOLIO1	0.77%	
54. feature BF_FORMR08		0.74%
55. feature RACE_K	0.71%	
56. feature BF_EXCLR06		0.70%
57. feature DROT3	0.66%	
58. feature LANGUAGE	0.64%	

59.	feature	FLU1_AGE	0.63%	
60.	feature	FLU2_AGE	0.61%	
61.	feature	DFLU3	0.60%	
62.	feature	DHEPB1	0.57%	
63.	feature	DTP4_AGE	0.56%	
64.	feature	PROV_FAC	0.53%	
65.	feature	I_HISP_K	0.52%	
66.	feature	INS_3A	0.51%	
67.	feature	HIB4_AGE	0.51%	
68.	feature	PCV4_AGE	0.50%	
69.	feature	HEA2_AGE	0.49%	
70.	feature	FLU3_AGE	0.48%	
71.	feature	HEP3_AGE	0.47%	
72.	feature	C5R	0.46%	
73.	feature	MMR1_AGE	0.46%	
74.	feature	HEA1_AGE	0.45%	
75.	feature	CEN_REG	0.44%	
76.	feature	DHEPB4	0.42%	
77.	feature	HEP2_AGE	0.42%	
78.	feature	INS_4_5	0.42%	
79.	feature	VRC1_AGE	0.41%	
80.	feature	P_NUMFLU	0.41%	
81.	feature	HIB3_AGE	0.41%	
82.	feature	NUM_PHONE		0.41%
83.	feature	P_NUMHS	0.40%	
84.	feature	P_NUMFLUN		0.37%
85.	feature	D6R	0.37%	
86.	feature	PCV3_AGE	0.36%	
87.	feature	POL3_AGE	0.36%	
88.	feature	P_NUMDIH	0.36%	
89.	feature	P_NUHIBX	0.35%	
90.	feature	INS_3	0.35%	
91.	feature	DTP3_AGE	0.33%	
92.	feature	REGISTRY	0.33%	
93.	feature	CHILDNM	0.33%	
94.	feature	P_NUHEPX	0.31%	
95.	feature	VFC_ORDER		0.31%
96.	feature	AGEGRP	0.31%	
97.	feature	P_NUMHM	0.31%	
98.	feature	P_NUMDTA	0.29%	
99.	feature	DPOLIO4	0.29%	
100.	feature	POL2_AGE		0.27%
101.	feature	P_NUMRM	0.27%	
102.	feature	PCV2_AGE		0.26%
103.	feature	P_NUMDHI		0.26%
104.	feature	XPOLTY2	0.25%	
105.	feature	HIB2_AGE		0.25%
106.	feature	PCV1_AGE		0.24%
107.	feature	ROT3_AGE		0.24%
108.	feature	HEP4_AGE		0.24%
109.	feature	DFLU4	0.24%	
110.	feature	DTP2_AGE		0.24%
111.	feature	P_NUMIPV		0.23%
112.	feature	XPOLTY3	0.23%	
113.	feature	HEP1_AGE		0.23%
114.	feature	FLU4_AGE		0.23%
115.	feature	ROT1_AGE		0.23%
116.	feature	P_NUMROT		0.23%
117.	feature	ROT2_AGE		0.22%

118.	feature	INS_11	0.22%	
119.	feature	XDTPTY3	0.22%	
120.	feature	P_NUMHEA		0.22%
121.	feature	XDTPTY1	0.21%	
122.	feature	N_PRVR	0.21%	
123.	feature	XPOLTY1	0.21%	
124.	feature	DTP1_AGE		0.21%
125.	feature	P_NUMHEP		0.21%
126.	feature	FRSTBRN	0.20%	
127.	feature	P_NUMRG	0.20%	
128.	feature	HIB1_AGE		0.20%
129.	feature	XDTPTY2	0.20%	
130.	feature	POL4_AGE		0.20%
131.	feature	SEX	0.20%	
132.	feature	P_NUMPCC13		0.20%
133.	feature	POL1_AGE		0.18%
134.	feature	P_NUMPCC		0.18%
135.	feature	P_NUMHIN		0.17%
136.	feature	XHEPTY3	0.17%	
137.	feature	P_NUMHIB		0.17%
138.	feature	XDTPTY4	0.17%	
139.	feature	XHEPTY4	0.17%	
140.	feature	P_NUMPOL		0.16%
141.	feature	U1D_HEP	0.16%	
142.	feature	CBF_01	0.15%	
143.	feature	INS_6	0.15%	
144.	feature	XHEPTY2	0.15%	
145.	feature	HEP_BRTH		0.15%
146.	feature	P_UTDHEPA2		0.15%
147.	feature	U2D_HEP	0.14%	
148.	feature	U3D_HEP	0.13%	
149.	feature	P_NUMPCV		0.13%
150.	feature	P_NUMMMRX		0.13%
151.	feature	P_UTDROT_S		0.12%
152.	feature	P_NUMDTP		0.12%
153.	feature	XMMRTY1	0.12%	
154.	feature	P_NUMVRX		0.12%
155.	feature	XPCVTY4	0.11%	
156.	feature	XHEPTY1	0.11%	
157.	feature	P_NUMFLUM		0.10%
158.	feature	XPCVTY1	0.10%	
159.	feature	P_UTDHEPA1		0.10%
160.	feature	XPCVTY2	0.10%	
161.	feature	XPCVTY3	0.09%	
162.	feature	P_UTDHIB_ROUT_S	0.09%	
163.	feature	P_UTD431H314_ROUT_S		0.09%
164.	feature	PU4313314	0.09%	
165.	feature	P_NUMMMR	0.08%	
166.	feature	P_NUMMMX	0.08%	
167.	feature	P_UTD431H3_ROUT_S		0.08%
168.	feature	PU431_314	0.08%	
169.	feature	P_UTD431H313_ROUT_S		0.08%
170.	feature	P_NUMMRV	0.08%	
171.	feature	P_UTD431H31_ROUT_S		0.08%
172.	feature	XPOLTY4	0.07%	
173.	feature	P_NUMVRC		0.07%
174.	feature	PU431331	0.07%	
175.	feature	P_NUMPCC7	0.07%	
176.	feature	P_UTD431	0.07%	

177.	feature	PU4313313	0.07%	
178.	feature	P_NUMRO	0.07%	
179.	feature	P_UTD431H_ROUT_S		0.07%
180.	feature	P_UTDTP4	0.07%	
181.	feature	PU431_31	0.06%	
182.	feature	PUTD4313	0.06%	
183.	feature	PUT43133	0.06%	
184.	feature	P_UTDPCV	0.06%	
185.	feature	P_NUMPCN	0.06%	
186.	feature	P_UTDMMX	0.05%	
187.	feature	P_NUMOLN	0.05%	
188.	feature	P_NUMTPN	0.05%	
189.	feature	DMMR2	0.05%	
190.	feature	MMR2_AGE	0.05%	
191.	feature	AGECPOXR	0.05%	
192.	feature	P_U12VRC	0.05%	
193.	feature	P_NUMFLUL	0.05%	
194.	feature	DVRC2	0.05%	
195.	feature	P_UTDMCV	0.05%	
196.	feature	P_UTD331	0.05%	
197.	feature	DTP5_AGE	0.04%	
198.	feature	VRC2_AGE	0.04%	
199.	feature	P_UTDHEP	0.04%	
200.	feature	DHIB5	0.04%	
201.	feature	P_UTDHIB	0.04%	
202.	feature	HAD_CPOX	0.04%	
203.	feature	P_NUMHION	0.04%	
204.	feature	DPCV5	0.04%	
205.	feature	DHEPB5	0.03%	
206.	feature	XMMRTY2	0.03%	
207.	feature	DDTP5	0.03%	
208.	feature	XHIBTY4	0.03%	
209.	feature	PCV5_AGE	0.03%	
210.	feature	DHEPA3	0.03%	
211.	feature	HIB5_AGE	0.03%	
212.	feature	P_UTDPOL	0.03%	
213.	feature	XHIBTY3	0.03%	
214.	feature	HEP5_AGE	0.03%	
215.	feature	HEA3_AGE	0.03%	
216.	feature	P_UTDHIB_SHORT_S		0.03%
217.	feature	XHEPTY5	0.02%	
218.	feature	P_UTDPC3	0.02%	
219.	feature	XPCVTY5	0.02%	
220.	feature	P_NUMHG	0.02%	
221.	feature	XDTPTY5	0.02%	
222.	feature	P_UTDTP3	0.02%	
223.	feature	XHIBTY1	0.02%	
224.	feature	P_NUMHHY	0.02%	
225.	feature	P_UTDPCVB13	0.02%	
226.	feature	D7	0.02%	
227.	feature	DFLU5	0.01%	
228.	feature	P_NUMMCN	0.01%	
229.	feature	DPOLIO5	0.01%	
230.	feature	P_NUMHEN	0.01%	
231.	feature	P_NUMDAH	0.01%	
232.	feature	P_NUHPHB	0.01%	
233.	feature	FLU5_AGE	0.01%	
234.	feature	XHIBTY2	0.01%	
235.	feature	P_NUMPCP	0.01%	

236.	feature	P_NUMVRN	0.01%
237.	feature	ROT4_AGE	0.01%
238.	feature	POL5_AGE	0.01%
239.	feature	P_NUMMS	0.01%
240.	feature	DROT4	0.01%
241.	feature	P_NUMOPV	0.01%
242.	feature	XPOLTY5	0.00%
243.	feature	DHIB6	0.00%
244.	feature	DPOLIO6	0.00%
245.	feature	FLU6_AGE	0.00%
246.	feature	XHEPTY6	0.00%
247.	feature	DFLU6	0.00%
248.	feature	PCV6_AGE	0.00%
249.	feature	DPCV6	0.00%
250.	feature	HEP_FLAG	0.00%
251.	feature	HIB6_AGE	0.00%
252.	feature	DVRC3	0.00%
253.	feature	HEP6_AGE	0.00%
254.	feature	XMMRTY3	0.00%
255.	feature	DDTP6	0.00%
256.	feature	HEA4_AGE	0.00%
257.	feature	XHEPTY7	0.00%
258.	feature	POL6_AGE	0.00%
259.	feature	MMR3_AGE	0.00%
260.	feature	PDAT	0.00%
261.	feature	DHEPA8	0.00%
262.	feature	XVRCTY8	0.00%
263.	feature	DHEPA9	0.00%
264.	feature	XVRCTY9	0.00%
265.	feature	YEAR	0.00%
266.	feature	DHEPA6	0.00%
267.	feature	P_NUMMSM	0.00%
268.	feature	BFFORMFL06	0.00%
269.	feature	BFENDFL06	0.00%
270.	feature	P_NUMMPR	0.00%
271.	feature	SHOTCARD	0.00%
272.	feature	DHEPA7	0.00%
273.	feature	XVRCTY3	0.00%
274.	feature	DHEPA5	0.00%
275.	feature	DDTP9	0.00%
276.	feature	P_NUMPCCN	0.00%
277.	feature	XVRCTY4	0.00%
278.	feature	XVRCTY5	0.00%
279.	feature	P_NUMRB	0.00%
280.	feature	DDTP7	0.00%
281.	feature	DDTP8	0.00%
282.	feature	DHEPB6	0.00%
283.	feature	DHEPA4	0.00%
284.	feature	P_NUMMP	0.00%
285.	feature	P_NUMMSR	0.00%
286.	feature	DFLU7	0.00%
287.	feature	DFLU8	0.00%
288.	feature	DFLU9	0.00%
289.	feature	XVRCTY6	0.00%
290.	feature	XVRCTY7	0.00%
291.	feature	XVRCTY2	0.00%
292.	feature	DHEPB7	0.00%
293.	feature	ROT7_AGE	0.00%
294.	feature	RB4_AGE	0.00%

295.	feature	RB5_AGE	0.00%
296.	feature	RB6_AGE	0.00%
297.	feature	RB7_AGE	0.00%
298.	feature	RB8_AGE	0.00%
299.	feature	RB9_AGE	0.00%
300.	feature	ROT5_AGE	0.00%
301.	feature	ROT6_AGE	0.00%
302.	feature	ROT8_AGE	0.00%
303.	feature	XDTPTY7	0.00%
304.	feature	ROT9_AGE	0.00%
305.	feature	VRC3_AGE	0.00%
306.	feature	VRC4_AGE	0.00%
307.	feature	VRC5_AGE	0.00%
308.	feature	VRC6_AGE	0.00%
309.	feature	VRC7_AGE	0.00%
310.	feature	VRC8_AGE	0.00%
311.	feature	VRC9_AGE	0.00%
312.	feature	RB3_AGE	0.00%
313.	feature	RB2_AGE	0.00%
314.	feature	RB1_AGE	0.00%
315.	feature	POL9_AGE	0.00%
316.	feature	MP7_AGE	0.00%
317.	feature	MP8_AGE	0.00%
318.	feature	MP9_AGE	0.00%
319.	feature	MPR1_AGE	0.00%
320.	feature	MPR2_AGE	0.00%
321.	feature	MPR3_AGE	0.00%
322.	feature	MPR4_AGE	0.00%
323.	feature	MPR5_AGE	0.00%
324.	feature	MPR6_AGE	0.00%
325.	feature	MPR7_AGE	0.00%
326.	feature	MPR8_AGE	0.00%
327.	feature	MPR9_AGE	0.00%
328.	feature	PCV7_AGE	0.00%
329.	feature	PCV8_AGE	0.00%
330.	feature	PCV9_AGE	0.00%
331.	feature	POL7_AGE	0.00%
332.	feature	POL8_AGE	0.00%
333.	feature	XDTPTY6	0.00%
334.	feature	XDTPTY8	0.00%
335.	feature	DHEPB8	0.00%
336.	feature	XPOLTY9	0.00%
337.	feature	XMMRTY9	0.00%
338.	feature	XPCVTY6	0.00%
339.	feature	XPCVTY7	0.00%
340.	feature	XPCVTY8	0.00%
341.	feature	XPCVTY9	0.00%
342.	feature	XPOLTY6	0.00%
343.	feature	XPOLTY7	0.00%
344.	feature	XPOLTY8	0.00%
345.	feature	XROTTY1	0.00%
346.	feature	XDTPTY9	0.00%
347.	feature	XROTTY2	0.00%
348.	feature	XROTTY3	0.00%
349.	feature	XROTTY4	0.00%
350.	feature	XROTTY5	0.00%
351.	feature	XROTTY6	0.00%
352.	feature	XROTTY7	0.00%
353.	feature	XROTTY8	0.00%

354.	feature	XROTTY9	0.00%
355.	feature	XMMRTY8	0.00%
356.	feature	XMMRTY7	0.00%
357.	feature	XMMRTY6	0.00%
358.	feature	XMMRTY5	0.00%
359.	feature	XFLUTY1	0.00%
360.	feature	XFLUTY2	0.00%
361.	feature	XFLUTY3	0.00%
362.	feature	XFLUTY4	0.00%
363.	feature	XFLUTY5	0.00%
364.	feature	XFLUTY6	0.00%
365.	feature	XFLUTY7	0.00%
366.	feature	XFLUTY8	0.00%
367.	feature	XFLUTY9	0.00%
368.	feature	XHEPTY8	0.00%
369.	feature	XHEPTY9	0.00%
370.	feature	XHIBTY5	0.00%
371.	feature	XHIBTY6	0.00%
372.	feature	XHIBTY7	0.00%
373.	feature	XHIBTY8	0.00%
374.	feature	XHIBTY9	0.00%
375.	feature	XMMRTY4	0.00%
376.	feature	MP6_AGE	0.00%
377.	feature	MP5_AGE	0.00%
378.	feature	MP4_AGE	0.00%
379.	feature	DPCV7	0.00%
380.	feature	DMPRB2	0.00%
381.	feature	DMPRB3	0.00%
382.	feature	DMPRB4	0.00%
383.	feature	DMPRB5	0.00%
384.	feature	DMPRB6	0.00%
385.	feature	DMPRB7	0.00%
386.	feature	DMPRB8	0.00%
387.	feature	DMPRB9	0.00%
388.	feature	DPCV8	0.00%
389.	feature	MP3_AGE	0.00%
390.	feature	DPCV9	0.00%
391.	feature	XVRCTY1	0.00%
392.	feature	DPOLIO7	0.00%
393.	feature	DPOLIO8	0.00%
394.	feature	DPOLIO9	0.00%
395.	feature	DRB1	0.00%
396.	feature	DRB2	0.00%
397.	feature	DRB4	0.00%
398.	feature	DMPRB1	0.00%
399.	feature	DMP9	0.00%
400.	feature	DMP8	0.00%
401.	feature	DMP7	0.00%
402.	feature	DHEPB9	0.00%
403.	feature	DHIB7	0.00%
404.	feature	DHIB8	0.00%
405.	feature	DHIB9	0.00%
406.	feature	DMMR3	0.00%
407.	feature	DMMR4	0.00%
408.	feature	DMMR5	0.00%
409.	feature	DMMR6	0.00%
410.	feature	DMMR7	0.00%
411.	feature	DMMR8	0.00%
412.	feature	DMMR9	0.00%



413.	feature DMP1	0.00%	
414.	feature DMP2	0.00%	
415.	feature DMP3	0.00%	
416.	feature DMP4	0.00%	
417.	feature DMP5	0.00%	
418.	feature DMP6	0.00%	
419.	feature DRB5	0.00%	
420.	feature DRB6	0.00%	
421.	feature DRB7	0.00%	
422.	feature HEA5_AGE		0.00%
423.	feature HEA7_AGE		0.00%
424.	feature HEA8_AGE		0.00%
425.	feature HEA9_AGE		0.00%
426.	feature HEP7_AGE		0.00%
427.	feature HEP8_AGE		0.00%
428.	feature HEP9_AGE		0.00%
429.	feature HIB7_AGE		0.00%
430.	feature HIB8_AGE		0.00%
431.	feature HIB9_AGE		0.00%
432.	feature MMR4_AGE		0.00%
433.	feature MMR5_AGE		0.00%
434.	feature MMR6_AGE		0.00%
435.	feature MMR7_AGE		0.00%
436.	feature MMR8_AGE		0.00%
437.	feature MMR9_AGE		0.00%
438.	feature MP1_AGE	0.00%	
439.	feature MP2_AGE	0.00%	
440.	feature HEA6_AGE		0.00%
441.	feature FLU9_AGE		0.00%
442.	feature DRB8	0.00%	
443.	feature FLU8_AGE		0.00%
444.	feature DRB9	0.00%	
445.	feature DROT5	0.00%	
446.	feature DROT6	0.00%	
447.	feature DROT7	0.00%	
448.	feature DROT8	0.00%	
449.	feature DROT9	0.00%	
450.	feature DVRC4	0.00%	
451.	feature DVRC5	0.00%	
452.	feature DVRC6	0.00%	
453.	feature DVRC7	0.00%	
454.	feature DVRC8	0.00%	
455.	feature DVRC9	0.00%	
456.	feature DTP6_AGE		0.00%
457.	feature DTP7_AGE		0.00%
458.	feature DTP8_AGE		0.00%
459.	feature DTP9_AGE		0.00%
460.	feature FLU7_AGE		0.00%
461.	feature DRB3	0.00%	

That looks much better! There are 14 features that are better than a random number. Those are going to be pulled out.

```
In [63]: top_ranks = feature_rank[:14]
top_ranks
```

```
Out[63]: [['INCQ298A', 0.0391078205871675],
          ['INCPORAR', 0.035646692927725536],
          ['CWIC_02', 0.028654993902786093],
          ['CWIC_01', 0.023230175100834492],
          ['INS_1', 0.02038651884983103],
          ['INCP0V1', 0.01993765656568219],
          ['RDDWT_D', 0.015504673576702621],
          ['PROVWT_D_TERR', 0.015420602721063194],
          ['INTRP', 0.015110562235401708],
          ['PROVWT_D', 0.014569486403276415],
          ['RDDWT_D_TERR', 0.014149759071087026],
          ['STRATUM', 0.014039891742704431],
          ['EDUC1', 0.013715384235440805],
          ['SEQNUMC', 0.012218604653439855]]
```

Creating a dataset with just those features AND the target, Rent Own

```
In [64]: top_rank_cols = [s[0].split(',')[0] for s in top_ranks]
          top_rank_cols.append('RENT_OWN')
          top_rank_cols
```

```
Out[64]: ['INCQ298A',
          'INCPORAR',
          'CWIC_02',
          'CWIC_01',
          'INS_1',
          'INCP0V1',
          'RDDWT_D',
          'PROVWT_D_TERR',
          'INTRP',
          'PROVWT_D',
          'RDDWT_D_TERR',
          'STRATUM',
          'EDUC1',
          'SEQNUMC',
          'RENT_OWN']
```

```
In [65]: # Creating a clean copy of the dataset to prevent messing with the OG set
          top_rank_df = df_rentown[top_rank_cols].copy()
```

```
In [66]: top_rank_df.head(10)
```

```
Out[66]:
```

	INCQ298A	INCPORAR	CWIC_02	CWIC_01	INS_1	INCPOV1	RDDWT_D	PROVWT_D_TERR	II
<b>1</b>	4	0.500000	0.0	2	2.0	3	454.860417	806.846012	
<b>3</b>	14	3.000000	0.0	2	1.0	1	36.965931	63.448686	
<b>4</b>	3	0.500000	1.0	1	2.0	3	64.620204	94.872632	
<b>5</b>	3	0.500000	1.0	1	2.0	3	85.219413	152.273845	
<b>6</b>	5	1.089867	1.0	1	2.0	2	112.170514	210.186351	
<b>7</b>	14	3.000000	0.0	2	1.0	1	142.607339	204.953336	
<b>8</b>	14	3.000000	0.0	2	1.0	1	499.775831	1016.753531	
<b>11</b>	10	1.438797	0.0	2	2.0	2	177.088881	390.532585	
<b>12</b>	9	1.481544	1.0	1	2.0	2	171.865720	248.745510	
<b>13</b>	5	0.639352	1.0	1	2.0	3	396.329703	489.064864	

Pair Plot of the data set

```
In [67]: sns.pairplot(data=top_rank_df)
```

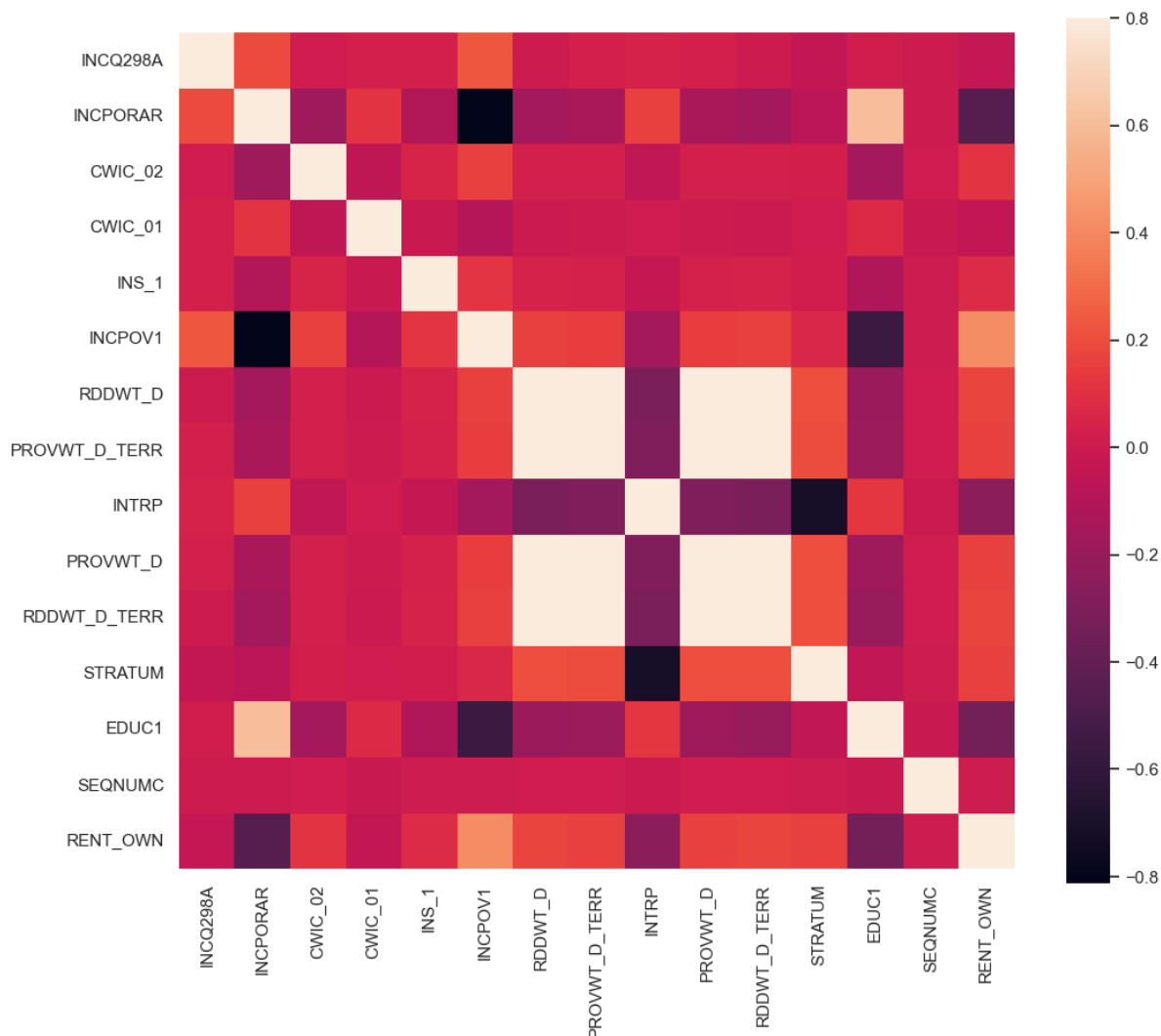
```
Out[67]: <seaborn.axisgrid.PairGrid at 0x1bb44b7fbb0>
```



New Correlation Matrix of the data

```
In [68]: corrmat = top_rank_df.corr()
f, ax = plt.subplots(figsize=(12,10)) #setting some parameters of the plot to help
sns.heatmap(corrmat, vmax = .8, square=True)
```

```
Out[68]: <Axes: >
```



Looking at the correlation plot, owning / renting a home are closely associated with income and education features.

```
In [69]: y = top_rank_df.RENT_OWN
x = top_rank_df.drop(['RENT_OWN'], axis=1)
```

```
In [70]: # Creating a 70/30 train test split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)

clf=RandomForestClassifier(n_estimators=100)
clf.fit(x_train,y_train)
```

```
Out[70]: ▼ RandomForestClassifier
RandomForestClassifier()
```

```
In [71]: y_pred=clf.predict(x_test)
```

```
In [72]: print("Accuracy:",metrics.accuracy_score(y_test, y_pred))

Accuracy: 0.7555299539170507
```

Unfortunately the accuracy of the model is only 75%. I am going to take a look at a new variable, marital status.

```
In [73]: df_marital = df_full
```

```
In [74]: y = df_marital.MARITAL2  
x = df_marital.drop(['MARITAL2'], axis=1)
```

```
In [75]: # Creating a 70/30 train test split  
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)  
  
clf=RandomForestClassifier(n_estimators=100)  
clf.fit(x_train,y_train)
```

```
Out[75]: ▼ RandomForestClassifier  
RandomForestClassifier()
```

```
In [76]: y_pred=clf.predict(x_test)
```

```
In [77]: print("Accuracy:",metrics.accuracy_score(y_test, y_pred))
```

Accuracy: 0.8488269145639663

All right, a model that gives an 85% accuracy. Let us see what the features are in the model.

```
In [78]: # Creating the random number  
np.random.seed(42)  
x['random'] = np.random.normal(0.0, 1.0, size=x.shape[0])
```

C:\Users\matth\AppData\Local\Temp\ipykernel\_18632\1480610971.py:3: PerformanceWarning: DataFrame is highly fragmented. This is usually the result of calling `frame.insert` many times, which has poor performance. Consider joining all columns at once using `pd.concat(axis=1)` instead. To get a de-fragmented frame, use `newframe = frame.copy()`

```
x['random'] = np.random.normal(0.0, 1.0, size=x.shape[0])
```

```
In [79]: # Checking that the random number was added  
x.head(10)
```

Out[79]:

	SEQNUMC	SEQNUMHH	PDAT	PROVWT_D	PROVWT_D_TERR	RDDWT_D	RDDWT_D_TERR	!
<b>1</b>	21	2	1	806.846012	806.846012	454.860417	454.860417	
<b>3</b>	41	4	1	63.448686	63.448686	36.965931	36.965931	
<b>4</b>	51	5	1	94.872632	94.872632	64.620204	64.620204	
<b>5</b>	52	5	1	152.273845	152.273845	85.219413	85.219413	
<b>6</b>	61	6	1	210.186351	210.186351	112.170514	112.170514	
<b>7</b>	71	7	1	204.953336	204.953336	142.607339	142.607339	
<b>8</b>	81	8	1	1016.753531	1016.753531	499.775831	499.775831	
<b>11</b>	111	11	1	390.532585	390.532585	177.088881	177.088881	
<b>12</b>	121	12	1	248.745510	248.745510	171.865720	171.865720	
<b>13</b>	131	13	1	489.064864	489.064864	396.329703	396.329703	

10 rows × 461 columns

```
In [80]: # Creating a 70/30 train test split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)

clf=RandomForestClassifier(n_estimators=100)
clf.fit(x_train,y_train)
```

Out[80]:

```
▼ RandomForestClassifier
RandomForestClassifier()
```

```
In [81]: # Running the random forest
features = x_train.columns
importances = clf.feature_importances_
std = np.std([tree.feature_importances_ for tree in clf.estimators_],
              axis=0)
indices = np.argsort(importances)[::-1]

# Save the feature ranking to a list for later use
# and print it on the screen

feature_rank = []
print("Feature ranking:")

for f in range(x_train.shape[1]):
    feature = f"{f + 1}. feature {features[indices[f]]} \t{importances[indices[f]]}"
    if 'random' in features[indices[f]]:
        feature += " <=="
    print(feature)
    feature_rank.append([features[indices[f]], importances[indices[f]]])
```

## Feature ranking:

1. feature INCQ298A	4.49%	
2. feature NUM_CELLS_PARENTS		4.21%
3. feature INCPORAR	3.56%	
4. feature CWIC_02	3.41%	
5. feature CWIC_01	3.28%	
6. feature INS_1	2.66%	
7. feature EDUC1	2.41%	
8. feature C1R	1.85%	
9. feature C5R	1.79%	
10. feature M_AGEGRP	1.73%	
11. feature NUM_CELLS_HH		1.69%
12. feature BF_ENDR06		1.65%
13. feature INCPOV1	1.47%	
14. feature PROVWT_D_TERR		1.18%
15. feature BF_FORMR08		1.17%
16. feature RDDWT_D	1.14%	
17. feature RENT_OWN	1.11%	
18. feature PROVWT_D	1.11%	
19. feature RDDWT_D_TERR		1.09%
20. feature INS_2	1.00%	
21. feature random	1.00%	<==
22. feature SEQNUMC	0.99%	
23. feature STRATUM	0.99%	
24. feature SEQNUMHH	0.97%	
25. feature ESTIAP14	0.95%	
26. feature INS_3A	0.86%	
27. feature EST_GRANT		0.86%
28. feature DFLU1	0.85%	
29. feature RACE_K	0.85%	
30. feature DVRC1	0.84%	
31. feature DHEPB2	0.84%	
32. feature DPCV4	0.83%	
33. feature DDTP4	0.83%	
34. feature DHIB3	0.81%	
35. feature DHIB4	0.81%	
36. feature DHEPB3	0.81%	
37. feature RACEETHK	0.81%	
38. feature DPOLIO3	0.80%	
39. feature DDTP3	0.80%	
40. feature DHEPA1	0.80%	
41. feature STATE	0.79%	
42. feature DMMR1	0.78%	
43. feature DPCV2	0.77%	
44. feature DDTP1	0.76%	
45. feature DPCV3	0.75%	
46. feature DROT2	0.72%	
47. feature DDTP2	0.71%	
48. feature DHEPA2	0.70%	
49. feature DHIB1	0.70%	
50. feature DPOLIO2	0.70%	
51. feature DHIB2	0.70%	
52. feature BF_EXCLR06		0.69%
53. feature DROT1	0.68%	
54. feature DPCV1	0.68%	
55. feature DFLU2	0.67%	
56. feature DPOLIO1	0.67%	
57. feature CBF_01	0.65%	
58. feature FLU1_AGE	0.57%	



59.	feature DROT3	0.56%	
60.	feature DTP4_AGE	0.52%	
61.	feature CHILDNM	0.52%	
62.	feature DHEPB1	0.51%	
63.	feature FLU2_AGE	0.50%	
64.	feature INS_3	0.49%	
65.	feature PCV4_AGE	0.47%	
66.	feature HEA2_AGE	0.47%	
67.	feature DFLU3	0.47%	
68.	feature HIB4_AGE	0.46%	
69.	feature LANGUAGE	0.44%	
70.	feature FLU3_AGE	0.44%	
71.	feature HEA1_AGE	0.44%	
72.	feature PROV_FAC	0.42%	
73.	feature HEP3_AGE	0.41%	
74.	feature I_HISP_K	0.39%	
75.	feature P_NUMFLUN		0.39%
76.	feature HIB3_AGE	0.38%	
77.	feature MMR1_AGE	0.38%	
78.	feature DHEPB4	0.38%	
79.	feature VRC1_AGE	0.37%	
80.	feature P_NUMHS	0.36%	
81.	feature CEN_REG	0.35%	
82.	feature FRSTBRN	0.35%	
83.	feature P_NUMFLU	0.35%	
84.	feature P_NUHIBX	0.34%	
85.	feature PCV3_AGE	0.32%	
86.	feature HEP2_AGE	0.31%	
87.	feature POL3_AGE	0.30%	
88.	feature DTP3_AGE	0.29%	
89.	feature P_NUMDTA	0.29%	
90.	feature AGEGRP	0.28%	
91.	feature REGISTRY	0.28%	
92.	feature VFC_ORDER		0.28%
93.	feature P_NUHEPX	0.27%	
94.	feature INTRP	0.27%	
95.	feature P_NUMDIH	0.27%	
96.	feature HIB2_AGE	0.26%	
97.	feature HEP4_AGE	0.25%	
98.	feature P_NUMRM	0.25%	
99.	feature P_NUMHM	0.24%	
100.	feature P_NUMROT		0.24%
101.	feature INS_11	0.24%	
102.	feature P_NUMDHI		0.23%
103.	feature XPOLTY2	0.23%	
104.	feature ROT2_AGE		0.23%
105.	feature DTP2_AGE		0.23%
106.	feature INS_4_5	0.22%	
107.	feature D6R	0.22%	
108.	feature P_NUMHEA		0.22%
109.	feature ROT3_AGE		0.21%
110.	feature POL2_AGE		0.21%
111.	feature POL1_AGE		0.21%
112.	feature XPOLTY1	0.21%	
113.	feature ROT1_AGE		0.20%
114.	feature HEP1_AGE		0.20%
115.	feature P_NUMIPV		0.19%
116.	feature DPOLIO4	0.19%	
117.	feature PCV1_AGE		0.19%

118.	feature	PCV2_AGE	0.19%	
119.	feature	NUM_PHONE	0.19%	
120.	feature	XDTPTY3	0.19%	
121.	feature	XPOLTY3	0.19%	
122.	feature	DFLU4	0.18%	
123.	feature	XDTPTY2	0.18%	
124.	feature	P_NUMPCC13	0.18%	
125.	feature	SEX	0.17%	
126.	feature	XDTPTY1	0.17%	
127.	feature	HIB1_AGE	0.17%	
128.	feature	P_NUMHEP	0.17%	
129.	feature	P_NUMRG	0.16%	
130.	feature	POL4_AGE	0.16%	
131.	feature	FLU4_AGE	0.16%	
132.	feature	DTP1_AGE	0.16%	
133.	feature	XHEPTY3	0.16%	
134.	feature	P_NUMHIB	0.15%	
135.	feature	XHEPTY4	0.15%	
136.	feature	N_PRVR	0.15%	
137.	feature	U2D_HEP	0.15%	
138.	feature	XDTPTY4	0.14%	
139.	feature	P_NUMPOL	0.14%	
140.	feature	XHEPTY2	0.14%	
141.	feature	P_NUMPCC	0.14%	
142.	feature	U1D_HEP	0.14%	
143.	feature	HEP_BRTH	0.13%	
144.	feature	P_UTDHEPA2	0.13%	
145.	feature	INS_6	0.13%	
146.	feature	P_NUMPCV	0.12%	
147.	feature	U3D_HEP	0.12%	
148.	feature	P_NUMHIN	0.11%	
149.	feature	P_NUMMMRX	0.11%	
150.	feature	MOBIL_I	0.11%	
151.	feature	P_NUMDTP	0.10%	
152.	feature	P_UTDROT_S	0.10%	
153.	feature	XMMRTY1	0.10%	
154.	feature	P_UTDHEPA1	0.10%	
155.	feature	P_NUMVRX	0.09%	
156.	feature	XHEPTY1	0.09%	
157.	feature	P_NUMMRV	0.08%	
158.	feature	XPCVTY2	0.08%	
159.	feature	XPCVTY4	0.08%	
160.	feature	XPCVTY1	0.08%	
161.	feature	P_NUMFLUM	0.08%	
162.	feature	P_NUMVRC	0.08%	
163.	feature	P_UTD431H313_ROUT_S	0.07%	
164.	feature	P_UTD431H3_ROUT_S	0.07%	
165.	feature	PU431_31	0.07%	
166.	feature	PU431331	0.07%	
167.	feature	XPCVTY3	0.07%	
168.	feature	P_NUMMMR	0.07%	
169.	feature	PU4313313	0.07%	
170.	feature	PU4313314	0.07%	
171.	feature	P_UTDHIB_ROUT_S	0.07%	
172.	feature	PUT43133	0.06%	
173.	feature	P_UTD431H_ROUT_S	0.06%	
174.	feature	P_UTD431H31_ROUT_S	0.06%	
175.	feature	PUTD4313	0.06%	
176.	feature	PU431_314	0.06%	

177.	feature	P_NUMMMX	0.06%	
178.	feature	P_NUMPCC7	0.06%	
179.	feature	P_UTDPCV	0.06%	
180.	feature	P_UTD431H314_ROUT_S		0.06%
181.	feature	P_UTDHEP	0.05%	
182.	feature	P_NUMPCN	0.05%	
183.	feature	P_UTDTP4	0.05%	
184.	feature	P_UTDMCV	0.05%	
185.	feature	P_UTD331	0.05%	
186.	feature	XPOLTY4	0.05%	
187.	feature	P_UTD431	0.05%	
188.	feature	P_NUMRO	0.05%	
189.	feature	VRC2_AGE	0.04%	
190.	feature	P_NUMOLN	0.04%	
191.	feature	P_NUMFLUL	0.04%	
192.	feature	P_UTDMMX	0.04%	
193.	feature	P_NUMTPN	0.04%	
194.	feature	P_U12VRC	0.04%	
195.	feature	DVRC2	0.04%	
196.	feature	P_UTDHIB	0.04%	
197.	feature	AGECPOXR	0.04%	
198.	feature	P_UTDPC3	0.03%	
199.	feature	DDTP5	0.03%	
200.	feature	DMMR2	0.03%	
201.	feature	P_UTDPOL	0.03%	
202.	feature	HAD_CPOX	0.03%	
203.	feature	P_NUMHION	0.03%	
204.	feature	DPCV5	0.03%	
205.	feature	DTP5_AGE	0.03%	
206.	feature	P_UTDTP3	0.03%	
207.	feature	XPCVTY5	0.02%	
208.	feature	P_UTDHIB_SHORT_S		0.02%
209.	feature	XHIBTY3	0.02%	
210.	feature	P_NUMHG	0.02%	
211.	feature	MMR2_AGE	0.02%	
212.	feature	P_NUMHHY	0.02%	
213.	feature	P_UTDPCVB13	0.02%	
214.	feature	PCV5_AGE	0.02%	
215.	feature	HEP5_AGE	0.02%	
216.	feature	HIB5_AGE	0.02%	
217.	feature	DHEPB5	0.02%	
218.	feature	XHEPTY5	0.02%	
219.	feature	DFLU5	0.02%	
220.	feature	P_NUMOPV	0.02%	
221.	feature	DHIB5	0.02%	
222.	feature	XHIBTY2	0.02%	
223.	feature	P_NUMHEN	0.02%	
224.	feature	FLU5_AGE	0.02%	
225.	feature	XDTPTY5	0.02%	
226.	feature	XMMRTY2	0.01%	
227.	feature	XHIBTY4	0.01%	
228.	feature	XHIBTY1	0.01%	
229.	feature	HEA3_AGE	0.01%	
230.	feature	P_NUMPCP	0.01%	
231.	feature	P_NUHPHB	0.01%	
232.	feature	DHEPA3	0.01%	
233.	feature	D7	0.01%	
234.	feature	POL5_AGE	0.01%	
235.	feature	P_NUMDAH	0.01%	

236.	feature	P_NUMMCN	0.01%
237.	feature	P_NUMMS	0.01%
238.	feature	P_NUMVRN	0.01%
239.	feature	DPOLIO5	0.01%
240.	feature	PCV6_AGE	0.00%
241.	feature	DPCV6	0.00%
242.	feature	HEP_FLAG	0.00%
243.	feature	DHEPB6	0.00%
244.	feature	XPOLTY5	0.00%
245.	feature	ROT4_AGE	0.00%
246.	feature	XHIBTY5	0.00%
247.	feature	DROT4	0.00%
248.	feature	DTP6_AGE	0.00%
249.	feature	HIB6_AGE	0.00%
250.	feature	HEP6_AGE	0.00%
251.	feature	DHEPA4	0.00%
252.	feature	DHIB6	0.00%
253.	feature	VRC3_AGE	0.00%
254.	feature	DVRC3	0.00%
255.	feature	XPCVTY6	0.00%
256.	feature	P_NUMPCCN	0.00%
257.	feature	MMR3_AGE	0.00%
258.	feature	FLU6_AGE	0.00%
259.	feature	P_NUMRB	0.00%
260.	feature	XVRCTY8	0.00%
261.	feature	P_NUMMSR	0.00%
262.	feature	DHEPA5	0.00%
263.	feature	DHEPA6	0.00%
264.	feature	XVRCTY4	0.00%
265.	feature	XROTTY7	0.00%
266.	feature	XVRCTY9	0.00%
267.	feature	XVRCTY5	0.00%
268.	feature	XVRCTY7	0.00%
269.	feature	DHEPA7	0.00%
270.	feature	DHEPA8	0.00%
271.	feature	DHEPA9	0.00%
272.	feature	XROTTY9	0.00%
273.	feature	XROTTY8	0.00%
274.	feature	BFENDFL06	0.00%
275.	feature	PDAT	0.00%
276.	feature	P_NUMMSM	0.00%
277.	feature	P_NUMMPR	0.00%
278.	feature	P_NUMMP	0.00%
279.	feature	BFFORMFL06	0.00%
280.	feature	XVRCTY3	0.00%
281.	feature	DDTP6	0.00%
282.	feature	DDTP7	0.00%
283.	feature	DDTP8	0.00%
284.	feature	DDTP9	0.00%
285.	feature	YEAR	0.00%
286.	feature	XVRCTY2	0.00%
287.	feature	XVRCTY1	0.00%
288.	feature	XROTTY5	0.00%
289.	feature	SHOTCARD	0.00%
290.	feature	DFLU6	0.00%
291.	feature	DFLU7	0.00%
292.	feature	DFLU8	0.00%
293.	feature	DFLU9	0.00%
294.	feature	XROTTY6	0.00%

295.	feature	XVRCTY6	0.00%	
296.	feature	XROTTY4	0.00%	
297.	feature	DHEPB7	0.00%	
298.	feature	POL7_AGE		0.00%
299.	feature	POL9_AGE		0.00%
300.	feature	RB1_AGE	0.00%	
301.	feature	RB2_AGE	0.00%	
302.	feature	RB3_AGE	0.00%	
303.	feature	RB4_AGE	0.00%	
304.	feature	RB5_AGE	0.00%	
305.	feature	RB6_AGE	0.00%	
306.	feature	RB7_AGE	0.00%	
307.	feature	RB8_AGE	0.00%	
308.	feature	RB9_AGE	0.00%	
309.	feature	ROT5_AGE		0.00%
310.	feature	ROT6_AGE		0.00%
311.	feature	ROT7_AGE		0.00%
312.	feature	ROT8_AGE		0.00%
313.	feature	ROT9_AGE		0.00%
314.	feature	VRC4_AGE		0.00%
315.	feature	VRC5_AGE		0.00%
316.	feature	POL8_AGE		0.00%
317.	feature	POL6_AGE		0.00%
318.	feature	MP2_AGE	0.00%	
319.	feature	PCV9_AGE		0.00%
320.	feature	MP4_AGE	0.00%	
321.	feature	MP5_AGE	0.00%	
322.	feature	MP6_AGE	0.00%	
323.	feature	MP7_AGE	0.00%	
324.	feature	MP8_AGE	0.00%	
325.	feature	MP9_AGE	0.00%	
326.	feature	MPR1_AGE		0.00%
327.	feature	MPR2_AGE		0.00%
328.	feature	MPR3_AGE		0.00%
329.	feature	MPR4_AGE		0.00%
330.	feature	MPR5_AGE		0.00%
331.	feature	MPR6_AGE		0.00%
332.	feature	MPR7_AGE		0.00%
333.	feature	MPR8_AGE		0.00%
334.	feature	MPR9_AGE		0.00%
335.	feature	PCV7_AGE		0.00%
336.	feature	PCV8_AGE		0.00%
337.	feature	VRC6_AGE		0.00%
338.	feature	VRC7_AGE		0.00%
339.	feature	VRC8_AGE		0.00%
340.	feature	VRC9_AGE		0.00%
341.	feature	XHIBTY9	0.00%	
342.	feature	XMMRTY3	0.00%	
343.	feature	XMMRTY4	0.00%	
344.	feature	XMMRTY5	0.00%	
345.	feature	XMMRTY6	0.00%	
346.	feature	XMMRTY7	0.00%	
347.	feature	XMMRTY8	0.00%	
348.	feature	XMMRTY9	0.00%	
349.	feature	XPCVTY7	0.00%	
350.	feature	XPCVTY8	0.00%	
351.	feature	XPCVTY9	0.00%	
352.	feature	XPOLTY6	0.00%	
353.	feature	XPOLTY7	0.00%	

354.	feature	XPOLTY8	0.00%
355.	feature	XPOLTY9	0.00%
356.	feature	XROTTY1	0.00%
357.	feature	XROTTY2	0.00%
358.	feature	XHIBTY8	0.00%
359.	feature	XHIBTY7	0.00%
360.	feature	XHIBTY6	0.00%
361.	feature	XFLUTY4	0.00%
362.	feature	XDTPTY6	0.00%
363.	feature	XDTPTY7	0.00%
364.	feature	XDTPTY8	0.00%
365.	feature	XDTPTY9	0.00%
366.	feature	XFLUTY1	0.00%
367.	feature	XFLUTY2	0.00%
368.	feature	XFLUTY3	0.00%
369.	feature	XFLUTY5	0.00%
370.	feature	XHEPTY9	0.00%
371.	feature	XFLUTY6	0.00%
372.	feature	XFLUTY7	0.00%
373.	feature	XFLUTY8	0.00%
374.	feature	XFLUTY9	0.00%
375.	feature	XHEPTY6	0.00%
376.	feature	XHEPTY7	0.00%
377.	feature	XHEPTY8	0.00%
378.	feature	MP3_AGE	0.00%
379.	feature	MP1_AGE	0.00%
380.	feature	DHEPB8	0.00%
381.	feature	DMP9	0.00%
382.	feature	DMPRB2	0.00%
383.	feature	DMPRB3	0.00%
384.	feature	DMPRB4	0.00%
385.	feature	DMPRB5	0.00%
386.	feature	DMPRB6	0.00%
387.	feature	DMPRB7	0.00%
388.	feature	DMPRB8	0.00%
389.	feature	DMPRB9	0.00%
390.	feature	DPCV7	0.00%
391.	feature	DPCV8	0.00%
392.	feature	DPCV9	0.00%
393.	feature	XROTTY3	0.00%
394.	feature	DPOLIO6	0.00%
395.	feature	DPOLIO7	0.00%
396.	feature	DPOLIO8	0.00%
397.	feature	DPOLIO9	0.00%
398.	feature	DRB1	0.00%
399.	feature	DMPRB1	0.00%
400.	feature	DMP8	0.00%
401.	feature	MMR9_AGE	0.00%
402.	feature	DMP7	0.00%
403.	feature	DHEPB9	0.00%
404.	feature	DHIB7	0.00%
405.	feature	DHIB8	0.00%
406.	feature	DHIB9	0.00%
407.	feature	DMMR3	0.00%
408.	feature	DMMR4	0.00%
409.	feature	DMMR5	0.00%
410.	feature	DMMR6	0.00%
411.	feature	DMMR7	0.00%
412.	feature	DMMR8	0.00%

413.	feature	DMMR9	0.00%	
414.	feature	DMP1	0.00%	
415.	feature	DMP2	0.00%	
416.	feature	DMP3	0.00%	
417.	feature	DMP4	0.00%	
418.	feature	DMP5	0.00%	
419.	feature	DMP6	0.00%	
420.	feature	DRB2	0.00%	
421.	feature	DRB4	0.00%	
422.	feature	DRB5	0.00%	
423.	feature	DRB6	0.00%	
424.	feature	HEA4_AGE		0.00%
425.	feature	HEA5_AGE		0.00%
426.	feature	HEA6_AGE		0.00%
427.	feature	HEA7_AGE		0.00%
428.	feature	HEA8_AGE		0.00%
429.	feature	HEA9_AGE		0.00%
430.	feature	HEP7_AGE		0.00%
431.	feature	HEP8_AGE		0.00%
432.	feature	HEP9_AGE		0.00%
433.	feature	HIB7_AGE		0.00%
434.	feature	HIB8_AGE		0.00%
435.	feature	HIB9_AGE		0.00%
436.	feature	MMR4_AGE		0.00%
437.	feature	MMR5_AGE		0.00%
438.	feature	MMR6_AGE		0.00%
439.	feature	MMR7_AGE		0.00%
440.	feature	MMR8_AGE		0.00%
441.	feature	FLU9_AGE		0.00%
442.	feature	FLU8_AGE		0.00%
443.	feature	FLU7_AGE		0.00%
444.	feature	DROT9	0.00%	
445.	feature	DRB7	0.00%	
446.	feature	DRB8	0.00%	
447.	feature	DRB9	0.00%	
448.	feature	DROT5	0.00%	
449.	feature	DROT6	0.00%	
450.	feature	DROT7	0.00%	
451.	feature	DROT8	0.00%	
452.	feature	DVRC4	0.00%	
453.	feature	DTP9_AGE		0.00%
454.	feature	DVRC5	0.00%	
455.	feature	DVRC6	0.00%	
456.	feature	DVRC7	0.00%	
457.	feature	DVRC8	0.00%	
458.	feature	DVRC9	0.00%	
459.	feature	DTP7_AGE		0.00%
460.	feature	DTP8_AGE		0.00%
461.	feature	DRB3	0.00%	

There are now 17 features that are better at predicting marital status than a randomw number. Unfortunately some of them are things like, "Number of cell phones in the house", and "Number of cell phones parents have".

```
In [82]: top_ranks = feature_rank[:17]
top_ranks
```

```
Out[82]: [['INCQ298A', 0.04493876505087042],
          ['NUM_CELLS_PARENTS', 0.04205578681194119],
          ['INCPORAR', 0.035614140113308386],
          ['CWIC_02', 0.034059552087169584],
          ['CWIC_01', 0.03281737474751377],
          ['INS_1', 0.026599281255561942],
          ['EDUC1', 0.024139091182115505],
          ['C1R', 0.018546259039010072],
          ['C5R', 0.017921462918803675],
          ['M_AGEGRP', 0.01726100006084509],
          ['NUM_CELLS_HH', 0.01690526401982556],
          ['BF_ENDR06', 0.016486299096405605],
          ['INCPOV1', 0.014730609307548475],
          ['PROVWT_D_TERR', 0.01182666975841087],
          ['BF_FORMR08', 0.011680061895478211],
          ['RDDWT_D', 0.01141982463766642],
          ['RENT_OWN', 0.011076082424101616]]
```

```
In [83]: top_rank_cols = [s[0].split(',')[0] for s in top_ranks]
top_rank_cols.append('MARITAL2')
top_rank_cols
```

```
Out[83]: ['INCQ298A',
          'NUM_CELLS_PARENTS',
          'INCPORAR',
          'CWIC_02',
          'CWIC_01',
          'INS_1',
          'EDUC1',
          'C1R',
          'C5R',
          'M_AGEGRP',
          'NUM_CELLS_HH',
          'BF_ENDR06',
          'INCPOV1',
          'PROVWT_D_TERR',
          'BF_FORMR08',
          'RDDWT_D',
          'RENT_OWN',
          'MARITAL2']
```

```
In [84]: top_rank_df = df_marital[top_rank_cols].copy()
```

```
In [85]: top_rank_df.head(10)
```



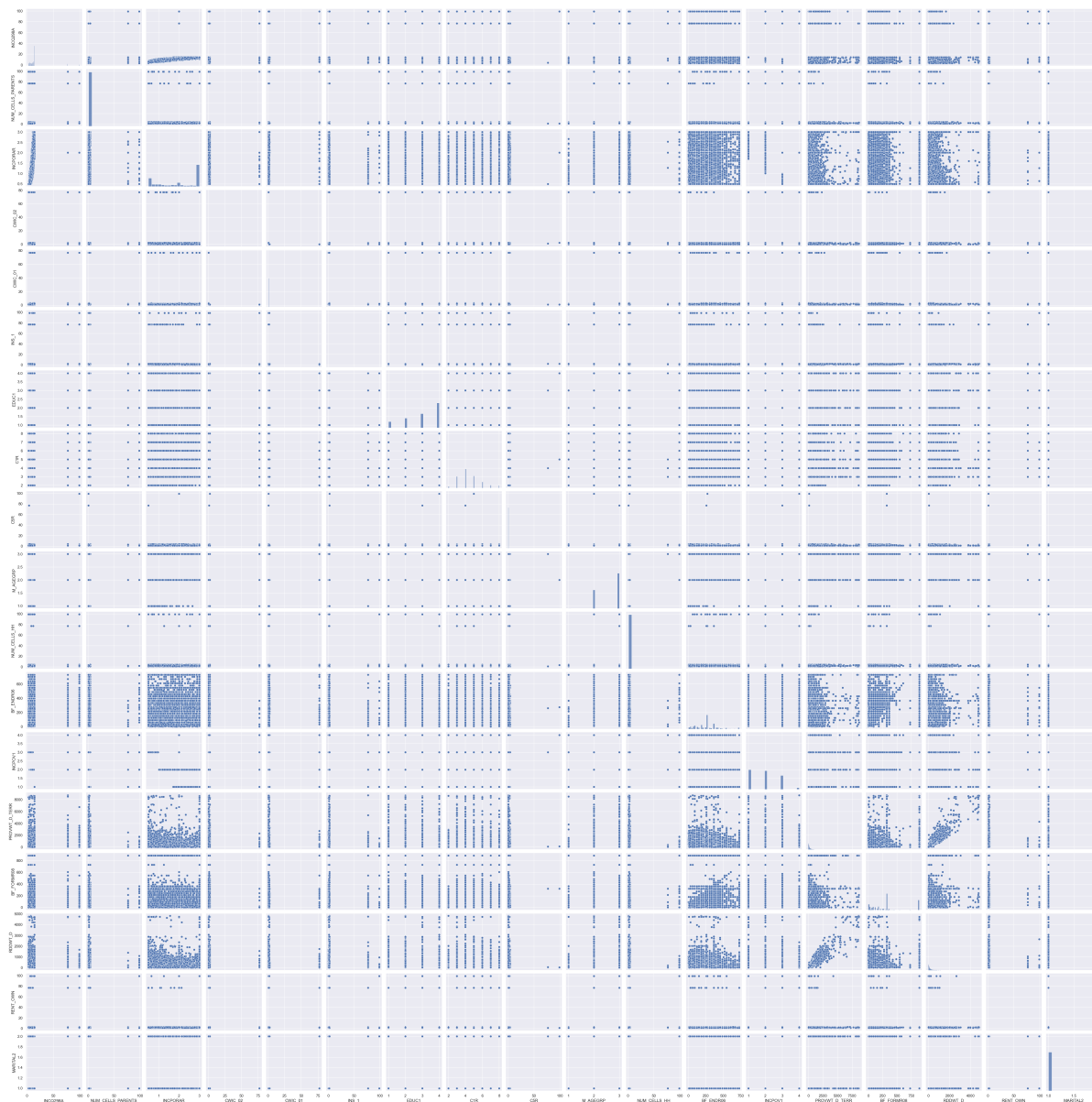
```
Out[85]:
```

	INCQ298A	NUM_CELLS_PARENTS	INCPORAR	CWIC_02	CWIC_01	INS_1	EDUC1	C1R	C5R
<b>1</b>	4	2.0	0.500000	0.0	2	2.0	2	6	1
<b>3</b>	14	2.0	3.000000	0.0	2	1.0	4	4	1
<b>4</b>	3	3.0	0.500000	1.0	1	2.0	2	8	3
<b>5</b>	3	3.0	0.500000	1.0	1	2.0	2	8	3
<b>6</b>	5	1.0	1.089867	1.0	1	2.0	3	2	3
<b>7</b>	14	2.0	3.000000	0.0	2	1.0	4	3	2
<b>8</b>	14	2.0	3.000000	0.0	2	1.0	4	3	1
<b>11</b>	10	2.0	1.438797	0.0	2	2.0	3	5	4
<b>12</b>	9	1.0	1.481544	1.0	1	2.0	3	4	1
<b>13</b>	5	1.0	0.639352	1.0	1	2.0	2	3	1

Marital Pair Plot

```
In [86]: sns.pairplot(data=top_rank_df)
```

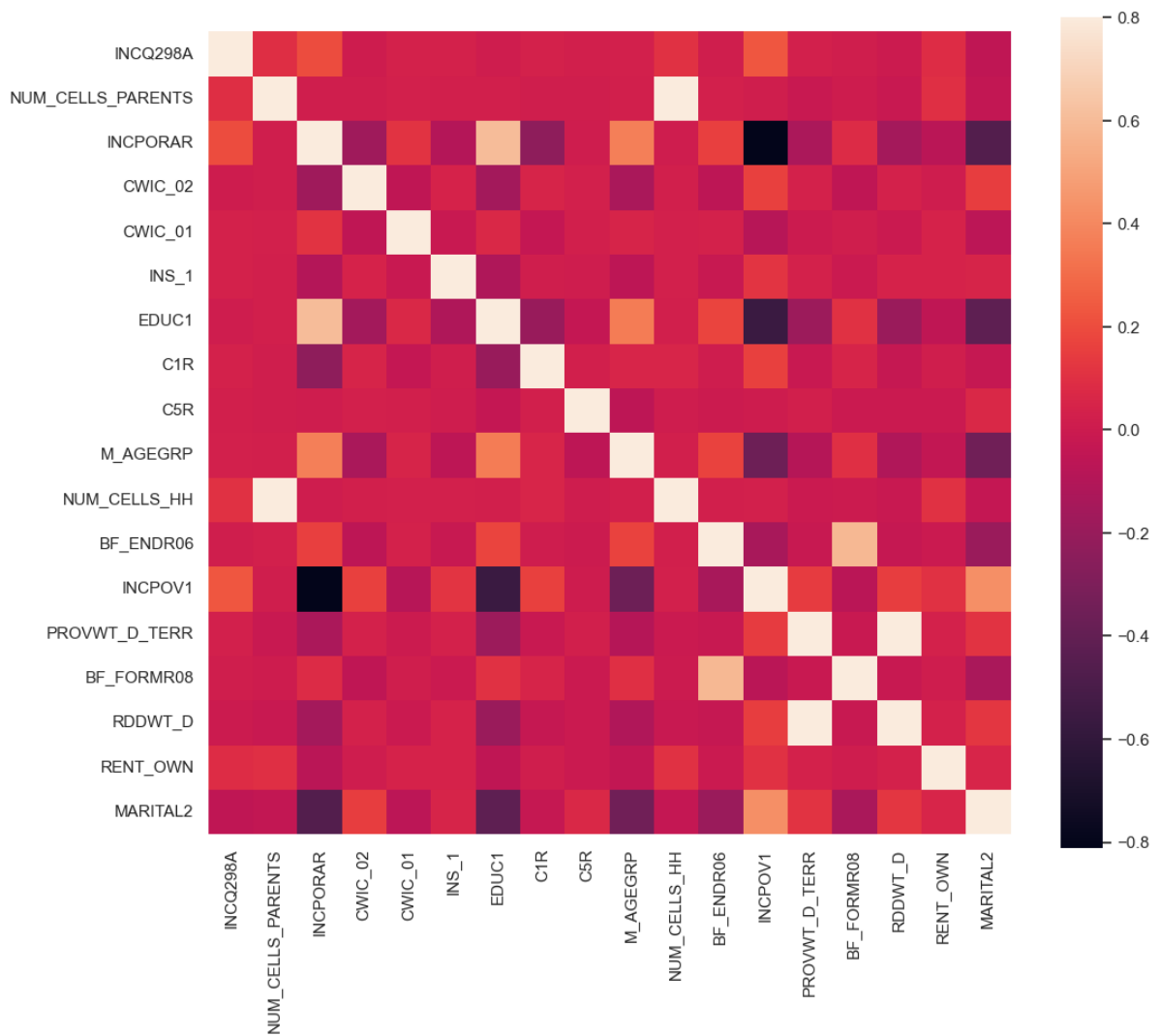
```
Out[86]: <seaborn.axisgrid.PairGrid at 0x1bb0d8ba1a0>
```



Marital Correlation Plot

```
In [87]: corrmat = top_rank_df.corr()
f, ax = plt.subplots(figsize=(12,10)) #setting some parameters of the plot to help
sns.heatmap(corrmat, vmax = .8, square=True)
```

```
Out[87]: <Axes: >
```



It looks like the, wic benefits and poverty status, are positively correlated and the, income to poverty ratio, marital age group, and education, are negatively correlated with marital status.

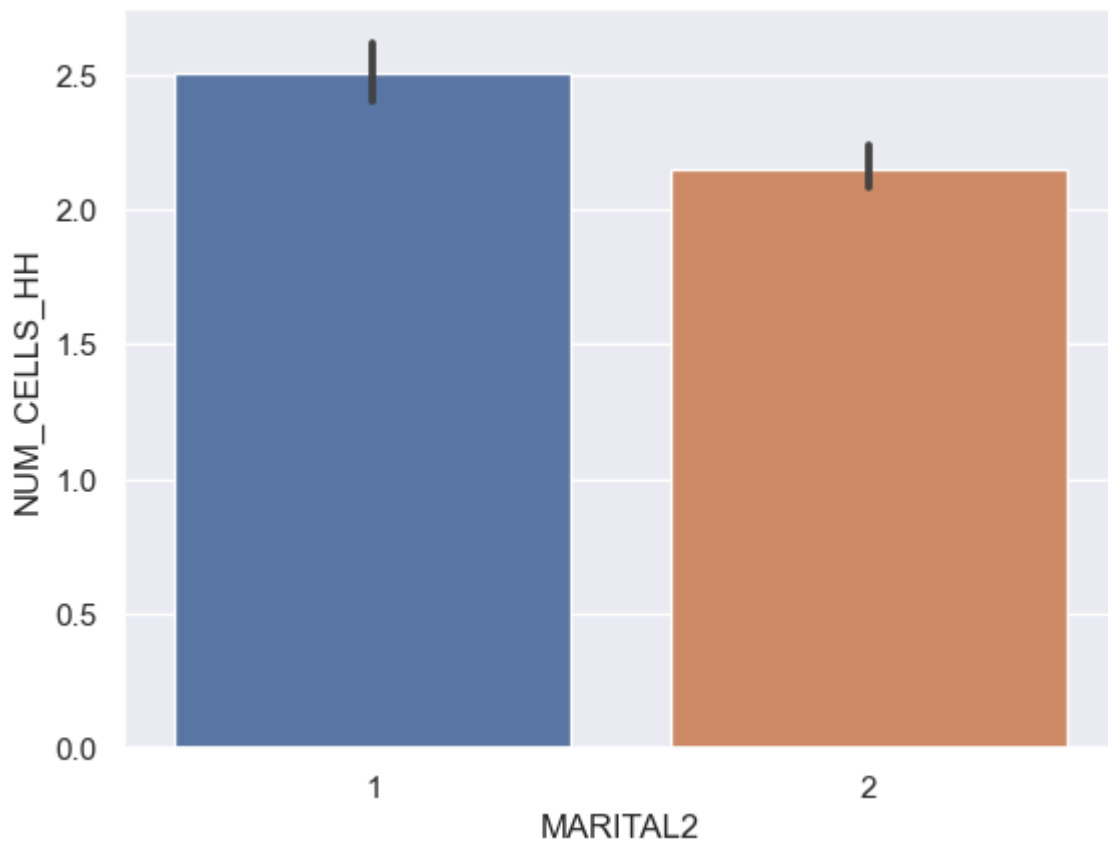
```
In [89]: marital = top_rank_df
marital.head(10)
```

```
Out[89]:
```

	INCQ298A	NUM_CELLS_PARENTS	INCPORAR	CWIC_02	CWIC_01	INS_1	EDUC1	C1R	C5R
<b>1</b>	4	2.0	0.500000	0.0	2	2.0	2	6	1
<b>3</b>	14	2.0	3.000000	0.0	2	1.0	4	4	1
<b>4</b>	3	3.0	0.500000	1.0	1	2.0	2	8	3
<b>5</b>	3	3.0	0.500000	1.0	1	2.0	2	8	3
<b>6</b>	5	1.0	1.089867	1.0	1	2.0	3	2	3
<b>7</b>	14	2.0	3.000000	0.0	2	1.0	4	3	2
<b>8</b>	14	2.0	3.000000	0.0	2	1.0	4	3	1
<b>11</b>	10	2.0	1.438797	0.0	2	2.0	3	5	4
<b>12</b>	9	1.0	1.481544	1.0	1	2.0	3	4	1
<b>13</b>	5	1.0	0.639352	1.0	1	2.0	2	3	1

```
In [93]: sns.barplot(x="MARITAL2", y="NUM_CELLS_HH", data=marital)
```

```
Out[93]: <Axes: xlabel='MARITAL2', ylabel='NUM_CELLS_HH'>
```

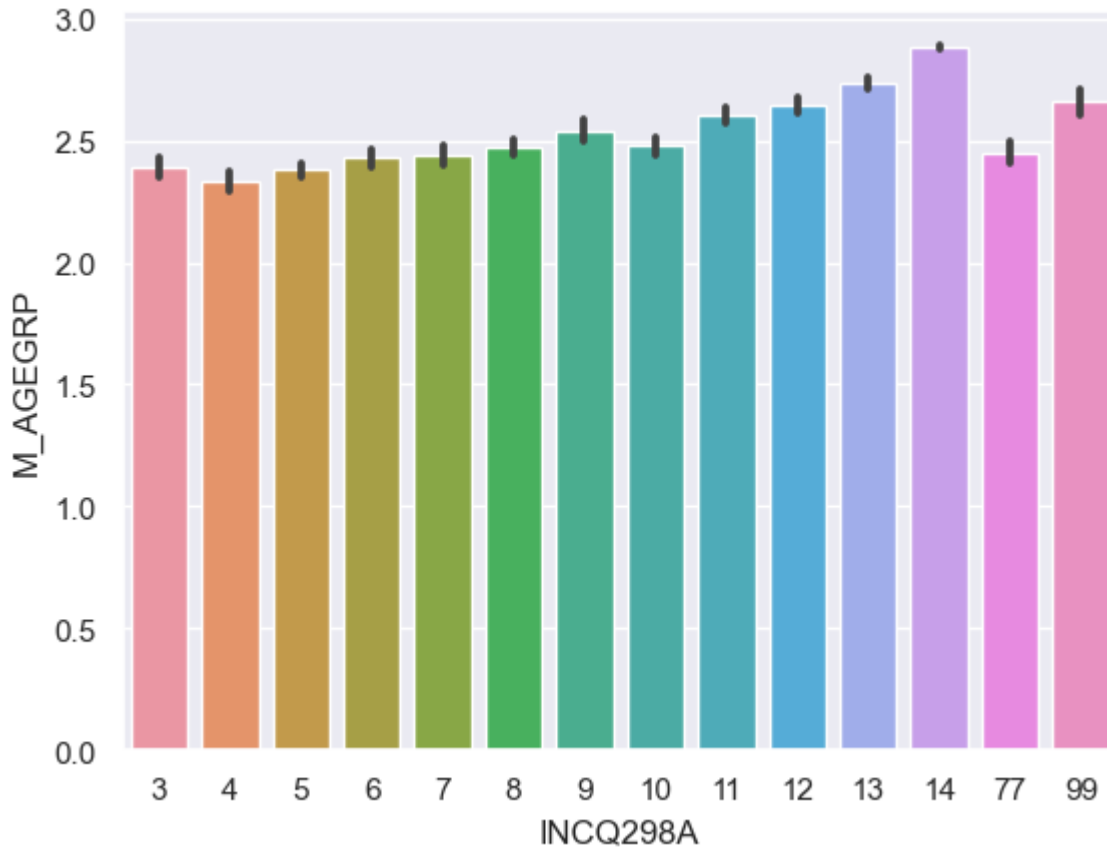


A look at number of cell phones compared to marital status. 1 is the married group, 2 is the not-married group. Bar in the confidence interval.

A look at income category compared to the years you have been married. This shows that the longer you have been married the higher your income is group.

```
In [115]: sns.barplot(x='INCQ298A', y='M_AGEGRP', data=marital)
```

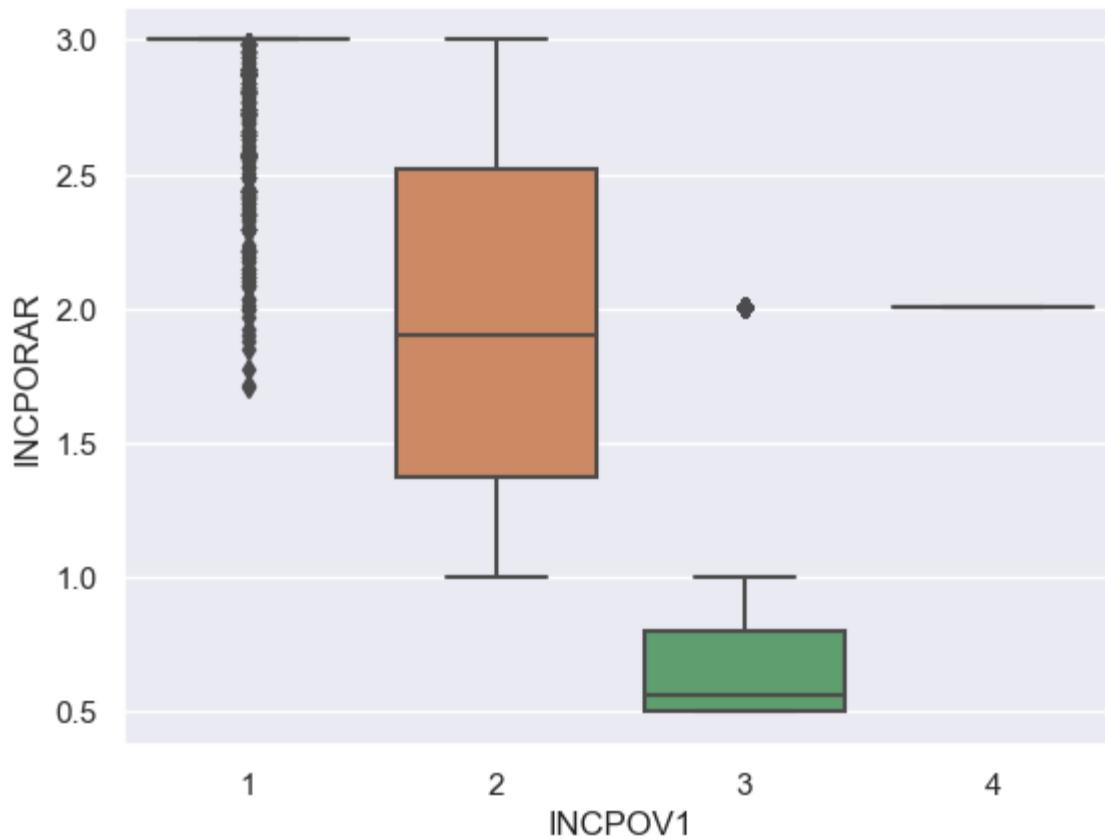
```
Out[115]: <Axes: xlabel='INCQ298A', ylabel='M_AGEGRP'>
```



A box plot of income to poverty ratio compared to Poverty status. Those in group 3 are Below the poverty line and have a very low income to poverty ratio.

```
In [121]: sns.boxplot(x='INCPV1', y='INCPORAR', data = marital)
```

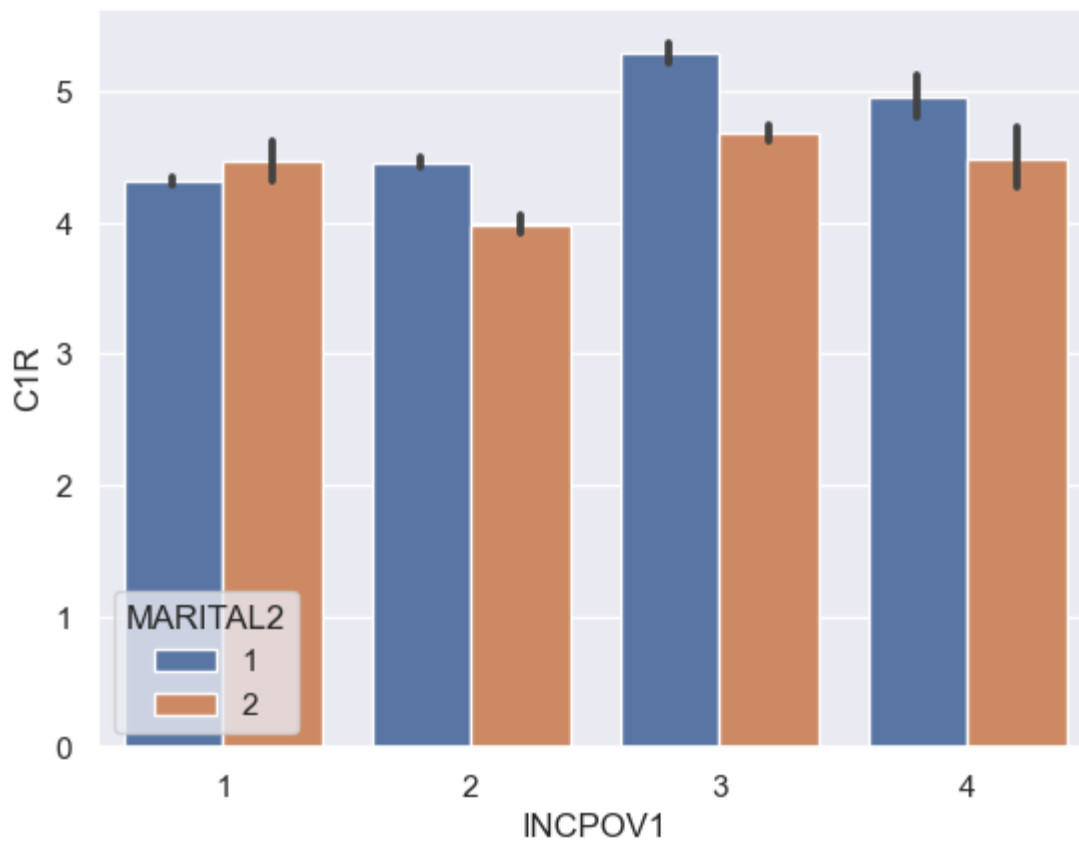
```
Out[121]: <Axes: xlabel='INCPV1', ylabel='INCPORAR'>
```



A look at the number of people in the household compared to poverty and marital status. Those who are Below Poverty Level (3) and married have the most people living in their houses. Those that are unmarried and above the poverty level, but below \$75k a year, have the least amount of people living in their houses.

```
In [123...] sns.barplot(x='INCPOV1',y='C1R', hue='MARITAL2', data=marital)
```

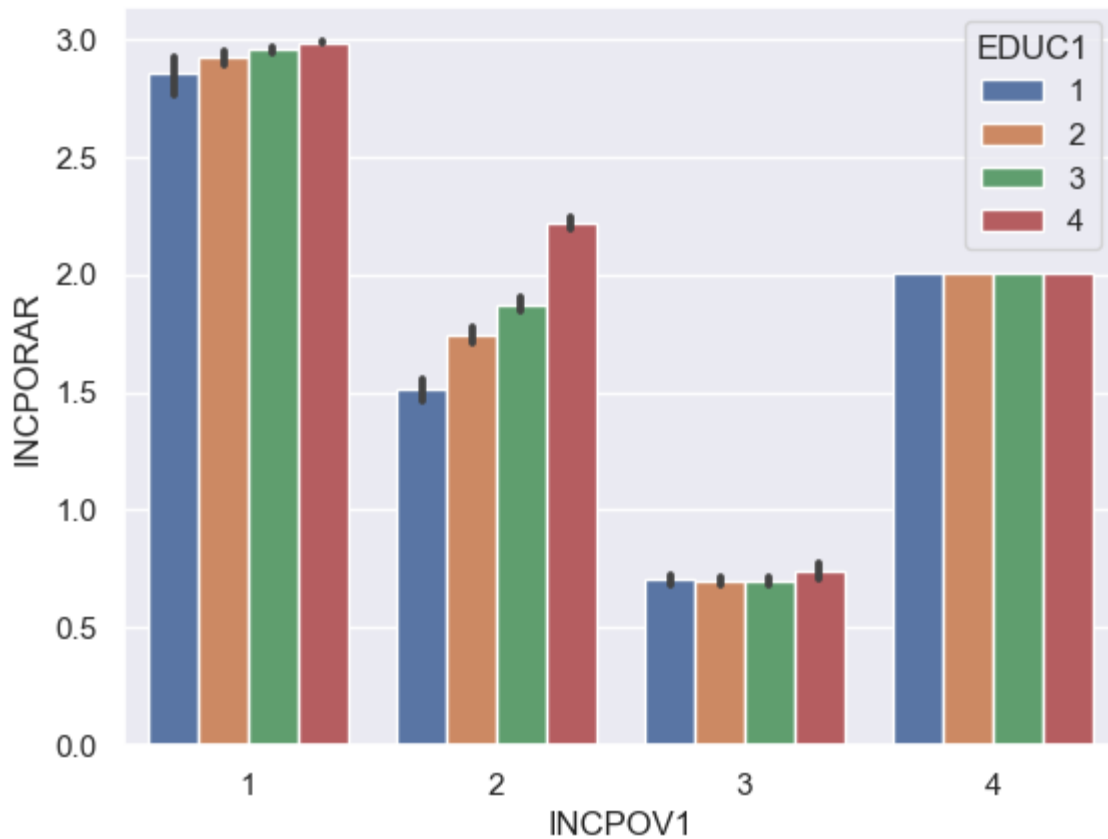
```
Out[123]: <Axes: xlabel='INCPOV1', ylabel='C1R'>
```



A look at education and poverty rate. Those with a 4 (College Grad) score the highest in each of the Income to poverty categories.

```
In [127...] sns.barplot(x='INCPOV1',y='INCPORAR', hue='EDUC1', data=marital)
```

```
Out[127]: <Axes: xlabel='INCPOV1', ylabel='INCPORAR'>
```



Dropping Variables: Based on the sns plot and correlation matrix several of the variables are going to be trimmed out due to having a low correlation. INCQ298A, the cell phone features, wic status, number of people in household C1R, and rent to own will all be dropped.

```
In [131...] small_marital = marital.drop(['INCQ298A', 'NUM_CELLS_PARENTS', 'CWIC_01', 'C1R', 'N
```

```
In [132...] small_marital.head(5)
```

```
Out[132]:
```

	INCPORAR	CWIC_02	INS_1	EDUC1	C5R	M_AGEGRP	BF_ENDR06	INCPOV1	PROVWT_D_TER1
1	0.500000	0.0	2.0	2	1	2	91.312500	3	806.84601
3	3.000000	0.0	1.0	4	1	3	334.812500	1	63.44868
4	0.500000	1.0	2.0	2	3	2	258.079564	3	94.87263
5	0.500000	1.0	2.0	2	3	2	258.079564	3	152.27384
6	1.089867	1.0	2.0	3	3	2	121.750000	2	210.18635

```
In [133...] y = marital.MARITAL2
x = marital.drop(['MARITAL2'], axis=1)
```

```
In [134...] # Creating a 70/30 train test split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)

clf=RandomForestClassifier(n_estimators=100)
clf.fit(x_train,y_train)
```



```
Out[134]: ▼ RandomForestClassifier  
RandomForestClassifier()
```

```
In [135... y_pred=clf.predict(x_test)
```

```
In [136... print("Accuracy:", metrics.accuracy_score(y_test, y_pred))
```

```
Accuracy: 0.8528109783089862
```

That slightly improved the model, by about 1%.

## Discussion / Conclusion

The biggest challenge in working with this dataset is the number of unknown values that it contained. I decided to start off by pairing down the data to just the rows that the paper said contained "Adequate Data". In retrospect this may not have been a good approach. When I started working I wanted to look at Chicken Pox and if it was affected by immunizations. I would have needed a data set that contained all the immunization information to have done so.

After running the random forest classifier with "Had Chicken Pox" as the target it was found that the data was unable to provide a good model, and that the strongest feature was at what age a child had had chicken pox.

I then repeated the random forest classifier with Owning or Renting a house, again the accuracy of the model was too low.

Finally I performed the random forest classifier with Marital Status as the target. This produced a model with 84.5% accuract using the 17 features that performed better than a random number. I paried this feature set down to 11 features which improved the models accuracy to 85.3%.

Visualization of model features is shown and includes the relationship between marital status and income, number of people living in the home, education, and poverty ratio.