This routine generates multiple social indicators at the municipal level for household surveys from 2011 to 2018.

Household surveys are created annually by the General Directorate of Statistics and Census. The survey allows generating indicators at the departmental level, however, there are 50 municipalities that are self-represented. In other words, the sample in these municipalities is large enough to be representative of themselves.

El Salvador has 262 municipalities, however in these 50 municipalities lives more than 65% of the population.

```
In [1]: import pandas as pd import numpy as np import os
```

GINI and the MEDIAN INCOME

I am interested in calculating the GINI and the median income in each municipality.

The survey calculates a frequency weighting for each respondent.

I have created a function that takes into account the frequency of each respondent. In addition, the GINI is calculated at the household income level and at the individual level.

```
In [2]: ####### defining the GINI indicator########
           \label{eq:def_gini} \textbf{def gini}(\texttt{EHPM, n\_deciles=10, hogar=False}):
                    "Calculate the GINI of household surveys in El Salvador"""
                x2 = EHPM[['ytot_ch','factor_ch','idp_ci','factor_ci','pc_ytot_ch']]
                #ytot_ch: Total household income
                #factor_ch: Weighted frequency of households
                #idp_ci: Type of survey (1=households; 0=individual)
#factor ci: Weighted frequency of individuals
                #pc_ytot_ch: Average income of each household member
                #defining the vars depending on the level required (Hogar: True = at the household level)
                if hogar==True:
                     x2 = x2[x2['idp_ci']==1]
                     x2['factor'] = x2['factor_ch']
x2['ytot'] = x2['ytot_ch']
                else:
                     x2['factor'] = x2['factor_ci']
x2['ytot'] = x2['pc_ytot_ch']
                ######sorting the data and creating the accumulated frequencies and then generating the deciles####
                x2 = x2[x2['ytot'].notna()]
x2 = x2.sort_values(by='ytot',ascending=True)
x2['ingre'] = x2['ytot']*x2['factor']
x2['x'] = x2['factor'].cumsum()/x2['factor'].sum()
                #creating a var for each decile
deciles = np.linspace(0, 1, n_deciles + 1)
                x2['deciles']=((pd.cut(x2['x'], deciles,labels=False))+1)
                #creating a table with the accumulated income in each decile and the expected income
                x3 = pd.pivot_table(x2,values='ingre',index=['deciles'],aggfunc=np.sum).reset_index()
x3['ingreso acumulado'] = x3['ingre'].cumsum()/x3['ingre'].sum()
x3['ingreso igualitario'] = x3['deciles']*(1/n_deciles)
                #calculating income difference between the accumulated per qunitil and the expected
                x3['dif']=x3['ingreso igualitario']-x3['ingreso acumulado']
                #calculating the difference relative to the total expected value (GINI)
                return x3.dif.sum()/x3['ingreso igualitario'].sum()
```

```
In [3]: ##### calculating the median of any indicator in the database, taking intoaccount the weighted frequency

def median(dataframe):
    """Extract the average of "values" given the weighted frequency "weights" (dataframe['values', 'weights'])"""

#sorting the data
    dataframe.sort_values(by=dataframe.columns[0], ascending=True, inplace=True)

#definind the vars
    values = dataframe.iloc[:,0]
    weights = dataframe.iloc[:,1]

#deleting data containing na values
    weights = weights[values.notna()]
    values = values.dropna()
    order = weights.cumsum()

#extrayendo el valor de la mediana
    median = values[order<=weights.sum()/2].max()

return median</pre>
```

```
In [5]: #Folder address
os.chdir(r'C:\Users\eleno\Documents\EHPM\Data')
```

Creating a routine for every survey

```
In [6]: #defining the years to use in each survey
year = ['2010','2011','2012','2013','2014','2015','2016','2017','2018']
#year =['2017','2018']
          #creating an empty dataframe to store the new data
          data = pd.DataFrame()
          for year in year:
               #reading the files in dta format
               x1 = pd.read_stata('SLV_'+year+'a_BID.dta', encoding='latin-1', convert_categoricals=False, convert_missing=False)
               #### Preparing the data
               #using data at the individual level
              x1 = x1[x1['miembros_ci']==1]
               #calculating total income
              x1['ytot_ci'] = x1[['ylm_ci','ylnm_ci','ynlm_ci','ynlnm_ci']].sum(axis=1)
               #calculating income per capita at each home
               x1['ytot_ch'] = x1.groupby('idh_ch')['ytot_ci'].transform('sum')
              x1.loc[x1.ytot_ch<=0,'ytot_ch']=np.nan
x1['pc_ytot_ch'] = x1['ytot_ch']/x1['nmiembros_ch']
               ###Extracting the municipality code from the survey
               #the variables created to define the municipalities is different depending on the survey
               #so I have built several cases to define the variable
               if (year=='2015')|(year=='2016')|(year=='2017')|(year=='2018'):
                   municipios = x1[x1['autorrepresentado']==1]['codigomunic'].drop_duplicates().values
                   if (municipios>100).sum()!=50:
                        x1['codigomunic']=x1['r005']
                        municipios = x1[x1['municauto']<50]['r005'].drop_duplicates().values</pre>
               if (year=='2011')|(year=='2012')|(year=='2013'):
                    x1['product']=100
                   x1['codigomunic']= x1['munic']+x1['product']*x1['region_c']
municipios = x1[x1['munic_auto']<50]['codigomunic'].drop_duplicates().values</pre>
               if year=='2014':
                   x1['codigomunic']=x1['municipio']
                   municipios = x1[x1['munic_auto']<50]['municipio'].drop_duplicates().values</pre>
               if year == '2010':
                   x1['product']=100
x1['codigomunic']= x1['munic_auto']+x1['product']*x1['region_c']
                   municipios = x1[x1['munic_auto']<50]['codigomunic'].drop_duplicates().values</pre>
               #calculating multiple indicators for each municipality
               for mun in municipios:
                   x = x1[x1['codigomunic']==mun]
                   #defining the year
                   anio = float(year)
                   #Average and median total income
                   y = x[['ytot_ci', 'factor_ci']][x['ytot_ci'].notna()] #droping na values
                   ytot_av = np.average(y['ytot_ci'],weights=y['factor_ci'])
ytot_med = median(y[['ytot_ci', 'factor_ci']])
                   #Average and median household income per capita
y = x[['ytot_ci', 'factor_ci', 'pc_ytot_ch']][(x['ytot_ci'].notna()) & (x['pc_ytot_ch'].notna())] #droping na values
pc_ytot_av = np.average(y['pc_ytot_ch'], weights=y['factor_ci'])
pc_ytot_med = median(y[['pc_ytot_ch', 'factor_ci']])
                   #Population
                   Population = x['factor_ci'].sum()
                   #Number of poor people in the municipality
                   pob_extr = x[x['pobreza']==1]['factor_ci'].sum()
pob_rela = x[x['pobreza']==2]['factor_ci'].sum()
no_pobre = x[x['pobreza']==3]['factor_ci'].sum()
                   #Percentage of household receiving remittances
                   remesas_percentage = x[x['remesas_ch']>0]['factor_ch'].sum()/x['factor_ch'].sum()
                   #Percentage of people working in differents sectors
                   #Percentage of economically active people
                   pea = x[x['pea_ci']==1]['factor_ch'].sum()/x['factor_ch'].sum()
                   #Number of unemployed people in the municipality
desempleo = x[x['desemp_ci']==1]['factor_ci'].sum()
                   empleo = x[x['desemp_ci']==0]['factor_ci'].sum()
                   #Number of people employed in the informal sector in the municipality informal = x[x['formal\_ci']=0]['factor\_ci'].sum()
                   formal = x[x['formal_ci']==1]['factor_ci'].sum()
                   #Years studied on average by population
y = x[['aedu_ci','factor_ci']][x['aedu_ci'].notna()]
                   escolar = np.average(y['aedu_ci'], weights=y['factor_ci'])
                   \label{eq:gini_ci} gini\_ci = gini(x,n\_deciles=10,hogar=False) \textit{\#calculating individual inequality}
                   \verb|gini_ch| = \verb|gini(x,n_deciles=10, hogar=True)| \textit{\#calculating household inequality}|
```

```
#storing the values created in the dataframe
          df = pd.DataFrame({'COD_MUN':mun,
                                 'Year': anio,
                                 'Average Income': ytot_av,
                                 'Median Income': ytot_med,
'Average Household Income per capita': pc_ytot_av,
                                 'Median Household Income per capita': pc_ytot_med,
                                 'Extreme poverty': pob_extr,
'Relative poverty': pob_rela,
'Not poor': no_pobre,
                                 'Unemployment': desempleo,
                                  'Working population':empleo,
                                  'Informal jobs': informal,
                                 'Formal jobs':formal,
                                 'Years of schooling': escolar,
                                 'Gini_ci': gini_ci,
'Gini_ch': gini_ch,
'Remittances %': remesas_percentage,
                                 'Agriculture workforce %': agriculture_wf,
'Industrial workforce %': industrial_wf,
'Services workforce %': services_wf,
'Economically active population %': pea,
                                 'Population':Population
                                },index=[0])
            #appending the data for each municipality
          data = data.append(df, ignore_index = True)
data = data.reset index(drop=True)
{\tt C:\Users\ELENOC\AppData\Local\Continuum\anaconda3\lib\site-packages\ipykernel\_launcher.py:7:\ SettingWithCopyWarning:} \\
A value is trying to be set on a copy of a slice from a DataFrame
```

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing-view-versus-copy import sys

 ${\tt C: \scale ENOC\appData\local \continuum\anaconda \lib\site-packages\ipykernel_launcher.py: 21: Setting \with \copyWarning: \color="block-right" continuum\anaconda \lib\site-packages\ipykernel_launcher.py: 21: Setting \with \color="block-right" continuum\anaconda \lib\site-packages\ipykernel\with \color="block-right" continuum\anaconda \lib\site-packages\ipykernel\with \color="block-right" continuum\anaconda \lib\site-packages\ipykernel\with \color="block-right" continuum\anaconda \lib\site-packages\ipykernel\with \color="bl$

A value is trying to be set on a copy of a slice from a DataFrame. Try using .loc[row indexer,col indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing-view-versus-copy C:\Users\ELENOC\AppData\Local\Continuum\anaconda3\lib\site-packages\ipykernel_launcher.py:22: SettingWithCopyWarning: A value is trying to be set on a copy of a slice from a DataFrame.

Try using .loc[row_indexer,col_indexer] = value instead

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

```
In [8]: #calculating job growth

#creating a table to facilitate iteration
x2 = pd.pivot_table(data, values='Working population',index=['COD_MUN'],columns=['Year'],aggfunc=np.sum).reset_index()

anios = np.arange(2011,2019)
anios2 = np.arange(2010,2018)

y2 = pd.DataFrame()

for x,y in zip(anios,anios2):
    y3 = pd.DataFrame()
    y3['yobs growth'] = (x2[x]-x2[y])/x2[y]
    y3['Year'] = x
    y3['COD_MUN'] = x2['COD_MUN']
    y2 = y2.append(y3)

#Merging the new variables
data = pd.merge(data,y2,on=['Year','COD_MUN'],how='inner')
```

Printing output data

In [9]: data.head()
Out[9]:

	COD_MUN	Year	Average Income	Median Income	Average Household Income per capita	Median Household Income per capita		Relative poverty	Not poor	Unemployment	 Remittances %		Industrial workforce %	workforce	Economically active population %	Population	Poverty ratio	Unemplo:
0	311	2011.0	148.904140	70.0	124.572034	100.933334	2911	9731	16791	642	 0.133422	0.081689	0.183189	0.375217	0.452281	29433	0.429518	0.0
1	202	2011.0	90.550311	0.0	79.882443	66.083333	8604	16538	14796	295	 0.138114	0.410612	0.169129	0.163220	0.422655	39938	0.629526	0.0
2	315	2011.0	138.954372	50.0	123.001383	83.333333	13052	27969	37494	1269	 0.090238	0.200042	0.115442	0.346083	0.435738	78515	0.522461	0.0
3	407	2011.0	162.465473	50.0	141.739855	104.616666	3305	7564	20789	813	 0.168172	0.217109	0.145772	0.235245	0.443679	31658	0.343326	0.0
4	501	2011.0	443.120287	196.0	390.837702	284.000000	692	4938	30677	576	 0.067232	0.033941	0.102316	0.268264	0.462996	36307	0.155067	0.0

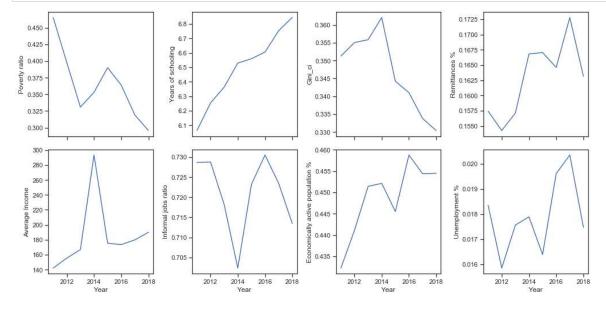
5 rows × 26 columns

Analyzing the data

1 Multiple ecatter plate to look for correlations

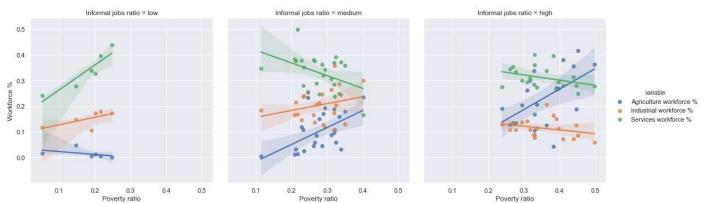
```
In [11]: import seaborn as sns; sns.set(style="ticks", color_codes=True)
                                                                           markers="+",
hue = 'Year')
                                                                                                            0.6 -
                                                                                            ठ<sub>।</sub>
5 <sub>0.4</sub>
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                         Year 2011.0 2012.0 2013.0 2014.0 2015.0 2016.0 2017.0 2018.0
                                                                                                                   8 -
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                                                                                                  0.35
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                                                                                                                                                                                                                                                                                                                                                   0.5 1.0
Informal jobs ratio
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                   0.75
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                0.3 0.4 0.5 0.6
Economically active population %
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                        0.0 0.5
Agriculture workforce %
```

2. How some indicators have changed during time

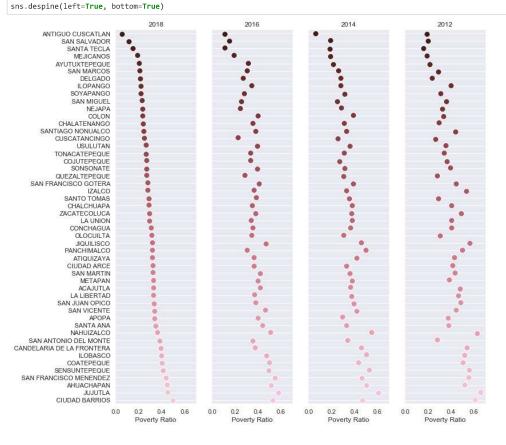


3. Observing correlation between poverty and economic classification of work in the municipalities in 2018

Out[13]: <seaborn.axisgrid.FacetGrid at 0x222850ea3c8>



```
data2 = pd.merge(data, inf_mun[['NOM_MUN','COD_MUN4','NOM_DPTO','REG_GEO_DE']],
left_on='COD_MUN',right_on='COD_MUN4',how='left')
          data2.rename(columns={'REG_GEO_DE':"Region", 'NOM_DPTO': "Departamento", 'NOM_MUN': "Municipio"}, inplace=True)
In [22]: #preparing data for the new graph
          df = pd.pivot_table(data2, values = 'Poverty ratio', index = 'Municipio', columns = 'Year', aggfunc=np.sum).reset_index()
          # Make the PairGrid
          g = sns.PairGrid(df.sort_values(2018, ascending=True),
                            x_vars=[2018,2016,2014,2012], y_vars=["Municipio"], height=10, aspect=.25)
          # Draw a dot plot using the stripplot function
          g.map(sns.stripplot, size=10, orient="h";
                palette="ch:s=1,r=-.1,h=1_r", linewidth=1, edgecolor="w")
          \# Use the same x axis limits on all columns and add better labels
          g.set(xlim=(0, 0.70), xlabel="Poverty Ratio", ylabel="")
          # Use semantically meaningful titles for the columns
          titles = [2018,2016,2014,2012]
          for ax, title in zip(g.axes.flat, titles):
              # Set a different title for each axes
              ax.set(title=title)
              # Make the grid horizontal instead of vertical
              ax.xaxis.grid(False)
              ax.yaxis.grid(True)
```



In [20]: | inf_mun = pd.read_csv("info_mun.csv", encoding = 'latin-1')

#merging the new data



fig.show()

