snap_finance_jupyter

January 22, 2020

1 Utah Poverty Analysis using SAIPE data

Outline of the Analysis - IRS data - Ranking all states by Mean and median AGI - Mean income and Mean income change over time for all states from IRS data - Change of Mean AGI,Tax exemptions of Utah and compare with highest and lowest AGI states - Ratio of poorto total exemption for Utah and compare with highest and lowest AGI states - ALLPOVU data - Year over year poverty for Utah and compare with differet age groups - Change of povert year over year - Utah County snapshot for July 2017 - SNAP Analysis - Compare Utah with with highest and lowest AGI states - Year over year change for foodstamp to population - Clustering to find similarities between states - Simple regression to find number of foodstamp users - Conclusion

Importing required modules

[1]:
```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
plt.style.use('seaborn-whitegrid')
from time import time
import datetime
import gc
import json
import plotly.figure_factory as ff
pd.set_option('display.max_columns', 1000)
import warnings
warnings.filterwarnings("ignore")
```

Loading data files

[2]:
```
file_path="/Users/krishanubanerjee/Downloads/snap_finance_project/"
irs=pd.read_excel(file_path+"/irs.xls",skiprows=2)
allpovu=pd.read_excel(file_path+"/allpovu.xls",skiprows=3)
cntysnap=pd.read_excel(file_path+"/cntysnap.xls",skiprows=2)
statesnap=pd.read_excel(file_path+"/statesnap.xls",skiprows=2)
#county_population=pd.read_csv(file_path+"county_population.csv")
```

External data - population from census

[3]:
```
county_population=pd.read_csv(file_path+"county_population.csv",encoding =␣
↪"ISO-8859-1")
pop_est_2018=pd.read_excel(file_path+"/pop_est_2018.xlsx",skiprows=3)
```

IRS data Analysis

[41]:
```
#irs.head()
```

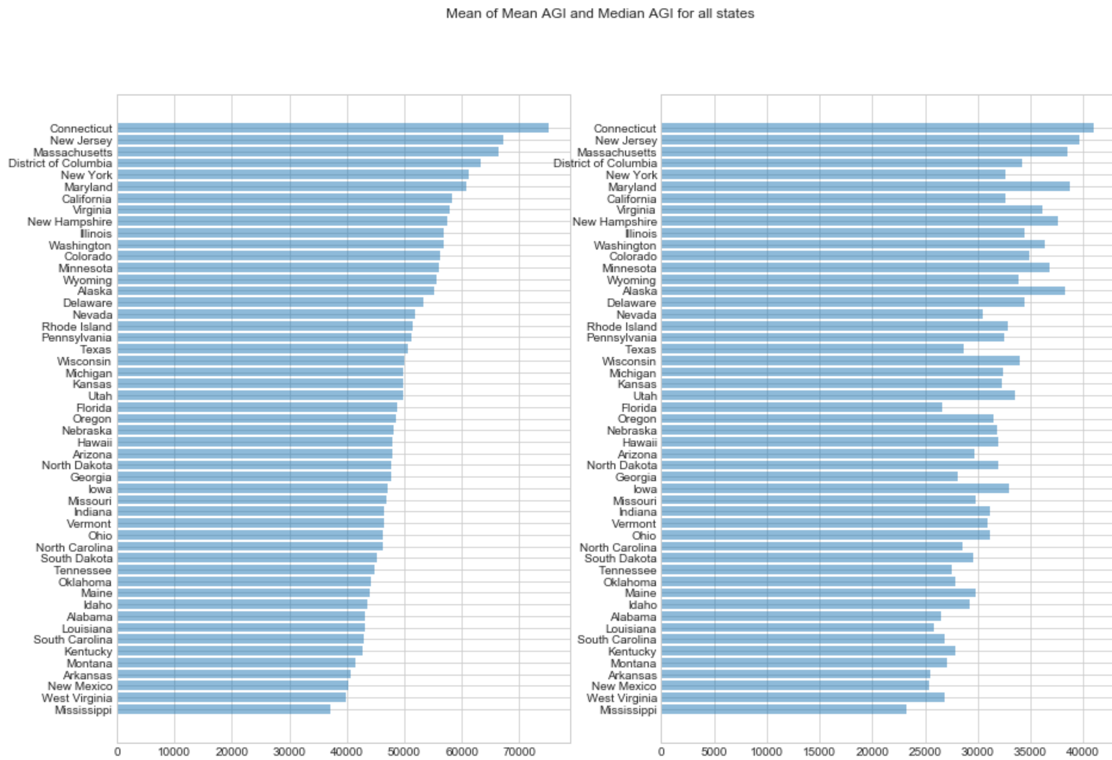
[17]:
```
irs.columns
```

[17]:
```
Index(['State FIPS code', 'Name', 'Year', 'Total exemptions',
       'Poor exemptions', 'Age 65 and over exemptions',
       'Age 65 and over poor exemptions', 'Child exemptions',
       'Poor child exemptions', 'Total exemptions under age 65',
       'Poor exemptions under age 65', 'Median AGI', 'Mean AGI'],
      dtype='object')
```

Ranking States average Mean AGI and Median AGI

[ ]:
```
# Unique states and years
irs_year=sorted(list(set(irs['Year'])))
irs_state=list(set(irs['Name']))

# Mean of mean AGI data
df=irs.groupby('Name').agg({'Mean AGI':'mean','Median AGI':'mean'}).
↪sort_values('Mean AGI',ascending=True)\
                        .reset_index()
```

[181]:
```
# Plot
fig, (ax1, ax2) = plt.subplots(1, 2,figsize=(15,10))
fig.suptitle('Mean of Mean AGI and Median AGI for all states')
ax1.barh(df['Name'], df['Mean AGI'], align='center', alpha=0.5)
ax2.barh(df['Name'], df['Median AGI'],align='center', alpha=0.5)
plt.show()
```



1) We can see Connecticut is highest mean for Mean AGI and Median AGI where Mississipi is the lowest 2) Utah is in middle 3) There are some states like Maryland or alaska where Median ranking is higher than Mean suggesting left skewed distribution

Year over year for all state and measures of IRS data

Year over year change percentage=100* ((Values of measure in year [i])- (Values of measure in year [i-1]) / (Values of measure in year [i])

[ ]:
```
def get_year_over_year_change(measure,state,plot=True):
    """
    This function will calculate year over year change percentage for a measure␣
↪for a state of irs data
    input : any measure from irs data, state and if plot is required
    output: list of change percentage and line plot
    """
    irs_year=sorted(list(set(irs['Year'])))
    change_over_year_list=[]
    for i in range(1,len(irs_year)):
        ␣
↪change_over_year=irs[measure][irs['Year']==irs_year[i]][irs['Name']==state].
↪values[0]- \
                        ␣
↪irs[measure][irs['Year']==irs_year[i-1]][irs['Name']==state].values[0]
```

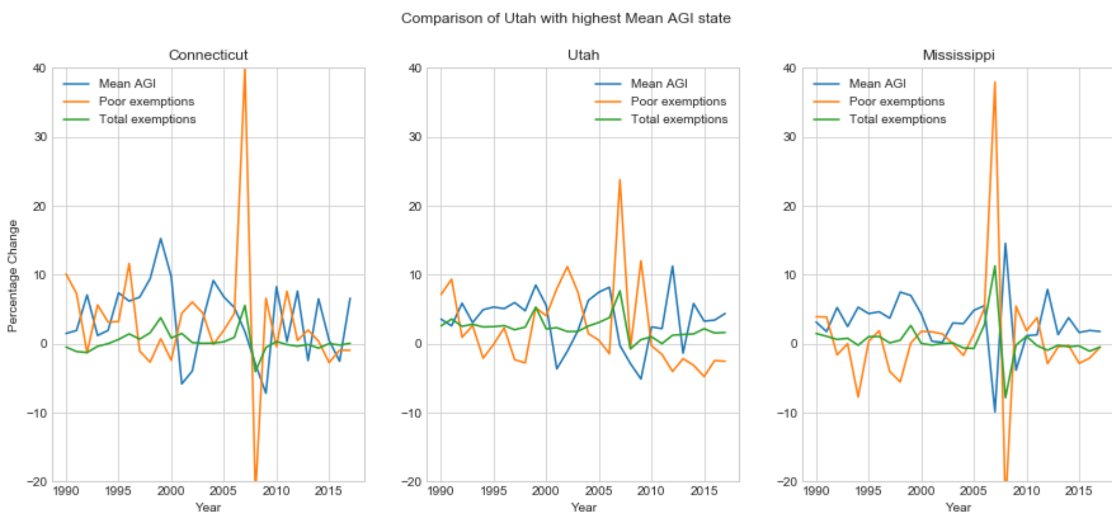
```
        change_over_year_prcnrg=100*round((change_over_year/
↪irs[measure][irs['Year']==irs_year[i-1]]\
                                   [irs['Name']==state].values[0]),4)
        change_over_year_list.append(change_over_year_prcnrg)


    if plot==True:
        fig = plt.figure(figsize=(10,8))
        ax = plt.axes()
        ax.plot(irs_year[1:len(irs_year)],change_over_year_list)
    return(change_over_year_list)
```

Comparison of Change Rate Year over Year for Mean AGI, Poor Exemptions and Total Exemptions

Utah against Highest and Lowest Mean AGI States

[206]:
```
# Plot
fig, (ax1,ax2,ax3) = plt.subplots(1, 3,figsize=(15,6))
fig.suptitle('Comparison of Utah with highest Mean AGI state')
ax1.plot(irs_year[1:len(irs_year)],get_year_over_year_change('Mean␣
↪AGI','Connecticut',plot=False),\
                                     label='Mean AGI')
ax1.plot(irs_year[1:len(irs_year)],get_year_over_year_change('Poor␣
↪exemptions','Connecticut',plot=False),\
                                     label='Poor exemptions')
ax1.plot(irs_year[1:len(irs_year)],get_year_over_year_change('Total␣
↪exemptions','Connecticut',plot=False),\
                                   label='Total exemptions')
ax1.set_ylim(-20, 40)
ax1.title.set_text('Connecticut')
ax1.set_xlabel('Year')
ax1.set_ylabel('Percentage Change')
ax1.legend()

ax2.plot(irs_year[1:len(irs_year)],get_year_over_year_change('Mean␣
↪AGI','Utah',plot=False),label='Mean AGI')
ax2.plot(irs_year[1:len(irs_year)],get_year_over_year_change('Poor␣
↪exemptions','Utah',plot=False),\
                                     label='Poor exemptions')
ax2.plot(irs_year[1:len(irs_year)],get_year_over_year_change('Total␣
↪exemptions','Utah',plot=False),\
                                   label='Total exemptions')
ax2.set_ylim(-20, 40)
ax2.title.set_text('Utah')
ax2.set_xlabel('Year')
```

```
ax2.legend()

ax3.plot(irs_year[1:len(irs_year)],get_year_over_year_change('Mean␣
↪AGI','Mississippi',plot=False),label='Mean AGI')
ax3.plot(irs_year[1:len(irs_year)],get_year_over_year_change('Poor␣
↪exemptions','Mississippi',plot=False),\
                                        label='Poor exemptions')
ax3.plot(irs_year[1:len(irs_year)],get_year_over_year_change('Total␣
↪exemptions','Mississippi',plot=False),\
                                      label='Total exemptions')
ax3.set_ylim(-20, 40)
ax3.title.set_text('Mississippi')
ax3.set_xlabel('Year')
plt.legend()
plt.show()
```



1) Around 2008 we can see spike in 'Poor Exemptions' for all states , probably impact of federal economy 2) 'Mean AGI' change is generally within +10% to -5% with some exeptions and state specific 3) 'Total Exemption' is very consistent 4) Is there any inverse relation between 'Poor Execmption' and 'Mean AGI' ? Is it a economic rule ? Need to analyse more to make general conclusion

Poor to total exemption ratio

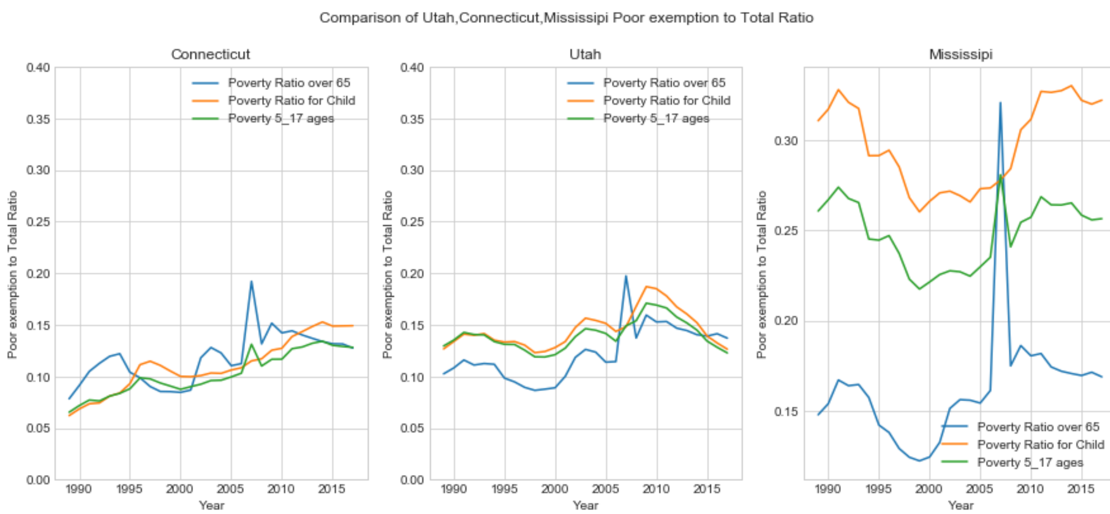
[218]:
```
def get_poor_to_total_ratio_data(state):
    """
    This function will get the ratio for poor exemtion to total exemption for␣
↪any category
    input - state
```

```
    output - dataframe with three derived ratios
    """
    df_irs=irs[irs['Name']==state]
    df_irs['over_65_ratio']=df_irs['Age 65 and over poor exemptions']/
 ↪df_irs['Age 65 and over exemptions']
    df_irs['child_ratio']=df_irs['Poor child exemptions']/df_irs['Child␣
 ↪exemptions']
    df_irs['under_65_ratio']=df_irs['Poor exemptions under age 65']/
 ↪df_irs['Total exemptions under age 65']
    return(df_irs)
```

[221]:

```
# Get data
df_irs_Utah=get_poor_to_total_ratio_data('Utah')
df_irs_Connecticut=get_poor_to_total_ratio_data('Connecticut')
df_irs_Mississippi=get_poor_to_total_ratio_data('Mississippi')

# Plot
fig, (ax1,ax2,ax3) = plt.subplots(1, 3,figsize=(15,6))
fig.suptitle('Comparison of Utah,Connecticut,Mississipi Poor exemption to Total␣
 ↪Ratio ')

ax1.plot(irs_year,df_irs_Connecticut['over_65_ratio'],label='Poverty Ratio over␣
 ↪65')
ax1.plot(irs_year,df_irs_Connecticut['child_ratio'],label='Poverty Ratio for␣
 ↪Child')
ax1.plot(irs_year,df_irs_Connecticut['under_65_ratio'],label='Poverty 5_17␣
 ↪ages')
ax1.set_ylim(0, .4)
ax1.title.set_text('Connecticut')
ax1.set_xlabel('Year')
ax1.set_ylabel('Poor exemption to Total Ratio')
ax1.legend()

ax2.plot(irs_year,df_irs_Utah['over_65_ratio'],label='Poverty Ratio over 65')
ax2.plot(irs_year,df_irs_Utah['child_ratio'],label='Poverty Ratio for Child')
ax2.plot(irs_year,df_irs_Utah['under_65_ratio'],label='Poverty 5_17 ages')
ax2.set_ylim(0, .4)
ax2.title.set_text('Utah')
ax2.set_xlabel('Year')
ax2.set_ylabel('Poor exemption to Total Ratio')
ax2.legend()


ax3.plot(irs_year,df_irs_Mississippi['over_65_ratio'],label='Poverty Ratio over␣
 ↪65')
```

```
ax3.plot(irs_year,df_irs_Mississippi['child_ratio'],label='Poverty Ratio for␣
↪Child')
ax3.plot(irs_year,df_irs_Mississippi['under_65_ratio'],label='Poverty 5_17␣
↪ages')
ax2.set_ylim(0, .4)
ax3.title.set_text('Mississipi')
ax3.set_xlabel('Year')
ax3.set_ylabel('Poor exemption to Total Ratio')
ax3.legend()
plt.show()
```



1) In general three states have different patterns except 2008 'Poverty Ratio over 65' spike 2) Before 2010, all ratios increased for Connecticut and Utah and after that it is decreasing for Utah and stable for Connecticut 3) Mississipi is showing complete different trend 4) Local economy impacts more in all states

allpovu analysis

[42]:
```
# Looking at data
#allpovu[allpovu['Name']=='Utah']
```

Data preperation

[228]:
```
def get_allpovu_by_state(state):
    """
    This function will flatten allpovu table filter for a state and return a␣
↪table with all variables
    with poverty Universe for different years
    input : state
```

```
    output : table with all poverty universe variables
    """
    year_list=[i for i in range(1998,2018)]
    povuAllages_list=[allpovu[allpovu['Name']==state]['Poverty Universe, All␣
↪Ages'].values[0]]
    povu_5_17_list=[allpovu[allpovu['Name']==state]['Poverty Universe, Age 5-17␣
↪related'].values[0]]
    povu_0_4_list=[allpovu[allpovu['Name']==state]['Poverty Universe, Age 0-4'].
↪values[0]]

    for i in range(1,20):
        povuAllages_list.append(allpovu[allpovu['Name']==state]['Poverty␣
↪Universe, All Ages.'+str(i)].values[0])
        povu_5_17_list.append(allpovu[allpovu['Name']==state]['Poverty␣
↪Universe, Age 5-17 related.'+str(i)].values[0])
        povu_0_4_list.append(allpovu[allpovu['Name']==state]['Poverty Universe,␣
↪Age 0-4.'+str(i)].values[0])

    df=pd.DataFrame(zip(year_list,povuAllages_list[::-1],povu_5_17_list[::
↪-1],povu_0_4_list[::-1])\
                    ,columns=['Year','povu_all_ages','povu_5_17','povu_0_4'])
    df['Ratio_0_4_to_all']=df['povu_0_4']/df['povu_all_ages']
    df['Ratio_5_17_to_all']=df['povu_5_17']/df['povu_all_ages']
    return(df)
```

[231]:
```
get_allpovu_by_state(state).head()
```

[231]:
```
   Year  povu_all_ages  povu_5_17  povu_0_4  Ratio_0_4_to_all  \
0  1998      2202474.0   495656.0  207660.0          0.094285
1  1999      2243729.0   492971.0  214244.0          0.095486
2  2000      2280291.0   505126.0  222505.0          0.097577
3  2001      2324130.0   504516.0  229963.0          0.098946
4  2002      2355997.0   499034.0  230778.0          0.097953

   Ratio_5_17_to_all
0           0.225045
1           0.219711
2           0.221518
3           0.217077
4           0.211814
```

[241]:
```
def get_year_over_year_change_allpovu(measure,state):
    """
    This function will calculate year over year change percentage
    """
    df=get_allpovu_by_state(state)
```

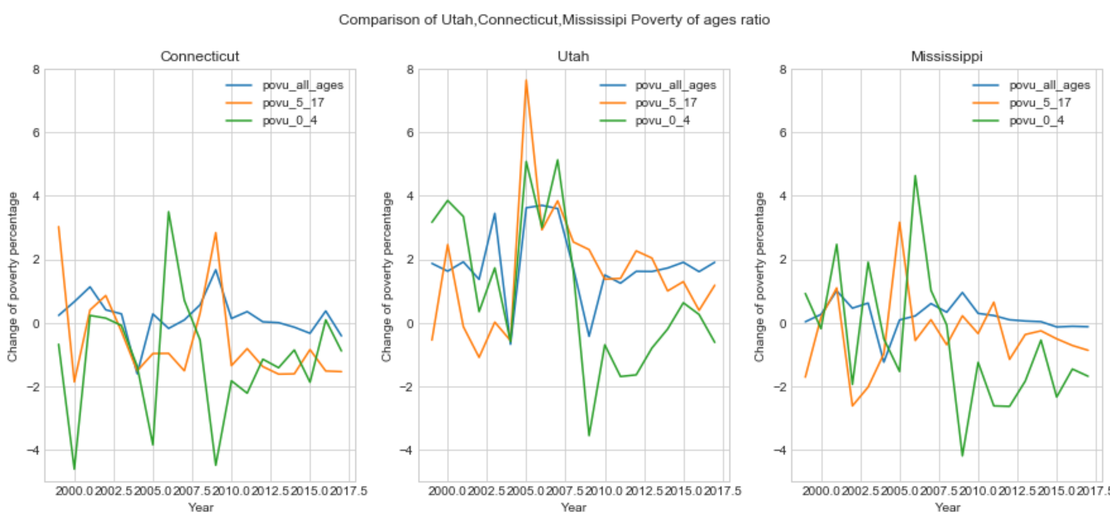
```
    year_list=[i for i in range(1998,2018)]
    change_over_year_list=[]
    for i in range(1,len(df['Year'])):
        change_over_year=df[measure][df['Year']==year_list[i]].values[0]- \
                       df[measure][df['Year']==year_list[i-1]].values[0]
        change_over_year_prcnrg=round(100*(change_over_year/
↪df[measure][df['Year']==year_list[i-1]]\
                                        .values[0]),4)
        change_over_year_list.append(change_over_year_prcnrg)

    return(change_over_year_list)
```

[248]:

```
#pov_all_Utah=get_year_over_year_change_allpovu('povu_all_ages','Utah')

fig, (ax1,ax2,ax3) = plt.subplots(1, 3,figsize=(15,6))
fig.suptitle('Comparison of Utah,Connecticut,Mississipi Poverty of ages ratio ')

ax1.plot([i for i in␣
↪range(1999,2018)],get_year_over_year_change_allpovu('povu_all_ages','Connecticut'),\
                                             label='povu_all_ages')
ax1.plot([i for i in␣
↪range(1999,2018)],get_year_over_year_change_allpovu('povu_5_17','Connecticut'),\
                                             label='povu_5_17')
ax1.plot([i for i in␣
↪range(1999,2018)],get_year_over_year_change_allpovu('povu_0_4','Connecticut'),\
                                             label='povu_0_4')
ax1.set_ylim(-5, 8)
ax1.title.set_text('Connecticut')
ax1.set_xlabel('Year')
ax1.set_ylabel('Change of poverty percentage')
ax1.legend()

ax2.plot([i for i in␣
↪range(1999,2018)],get_year_over_year_change_allpovu('povu_all_ages','Utah'),\
                                             label='povu_all_ages')
ax2.plot([i for i in␣
↪range(1999,2018)],get_year_over_year_change_allpovu('povu_5_17','Utah'),\
                                             label='povu_5_17')
ax2.plot([i for i in␣
↪range(1999,2018)],get_year_over_year_change_allpovu('povu_0_4','Utah'),\
                                             label='povu_0_4')
ax2.set_ylim(-5, 8)
ax2.title.set_text('Utah')
ax2.set_xlabel('Year')
ax2.set_ylabel('Change of poverty percentage')
ax2.legend()
```

```
ax3.plot([i for i in␣
↪range(1999,2018)],get_year_over_year_change_allpovu('povu_all_ages','Mississippi'),\
                                                        label='povu_all_ages')
ax3.plot([i for i in␣
↪range(1999,2018)],get_year_over_year_change_allpovu('povu_5_17','Mississippi'),\
                                                        label='povu_5_17')
ax3.plot([i for i in␣
↪range(1999,2018)],get_year_over_year_change_allpovu('povu_0_4','Mississippi'),\
                                                        label='povu_0_4')
ax3.set_ylim(-5, 8)
ax3.title.set_text('Mississippi')
ax3.set_xlabel('Year')
ax3.set_ylabel('Change of poverty percentage')
ax3.legend()
```

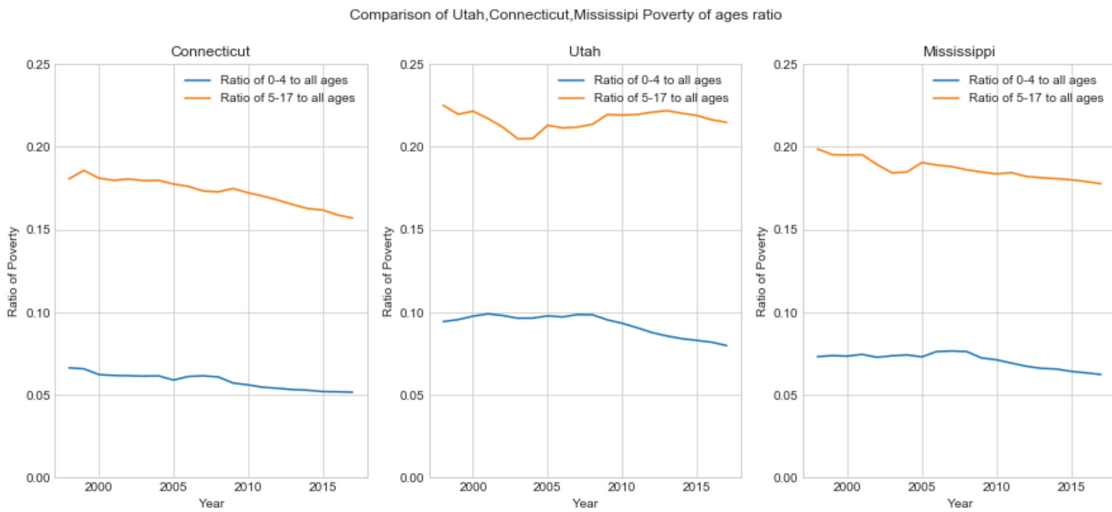
[248]: <matplotlib.legend.Legend at 0x1228af050>



1) In general poverty is not increasing after 2010 2) In general poverty for 0-4 age is decreasing which is good

[230]:
```
## get data
df_allpovu_Connecticut=get_allpovu_by_state('Connecticut')
df_allpovu_Utah=get_allpovu_by_state('Utah')
df_allpovu_Mississippi=get_allpovu_by_state('Mississippi')

# Plot
fig, (ax1,ax2,ax3) = plt.subplots(1, 3,figsize=(15,6))
fig.suptitle('Comparison of Utah,Connecticut,Mississipi Poverty of ages ratio ')
```

```
ax1.
↪plot(df_allpovu_Connecticut['Year'],df_allpovu_Connecticut['Ratio_0_4_to_all'],label='Ratio
↪of 0-4 to all ages')
ax1.
↪plot(df_allpovu_Connecticut['Year'],df_allpovu_Connecticut['Ratio_5_17_to_all'],label='Rati
↪of 5-17 to all ages')
ax1.set_ylim(0, .25)
ax1.title.set_text('Connecticut')
ax1.set_xlabel('Year')
ax1.set_ylabel('Ratio of Poverty')
ax1.legend()

ax2.
↪plot(df_allpovu_Utah['Year'],df_allpovu_Utah['Ratio_0_4_to_all'],label='Ratio␣
↪of 0-4 to all ages')
ax2.
↪plot(df_allpovu_Utah['Year'],df_allpovu_Utah['Ratio_5_17_to_all'],label='Ratio␣
↪of 5-17 to all ages')
ax2.set_ylim(0, .25)
ax2.title.set_text('Utah')
ax2.set_xlabel('Year')
ax2.set_ylabel('Ratio of Poverty')
ax2.legend()

ax3.
↪plot(df_allpovu_Mississippi['Year'],df_allpovu_Mississippi['Ratio_0_4_to_all'],label='Ratio
↪of 0-4 to all ages')
ax3.
↪plot(df_allpovu_Mississippi['Year'],df_allpovu_Mississippi['Ratio_5_17_to_all'],label='Rati
↪of 5-17 to all ages')
ax3.set_ylim(0, .25)
ax3.title.set_text('Mississippi')
ax3.set_xlabel('Year')
ax3.set_ylabel('Ratio of Poverty')
ax3.legend()
plt.show()
```



In general for all states povert percentage for kids decreasing -that is good

cntysnap Want to focus on number of people taken foodstamp in different counties of utah on 2017 july

[4]:
```
# get data
utah_july_snap=cntysnap[(cntysnap['State FIPS code']==49)&(cntysnap['County␣
↪FIPS code']!=0)]
utah_july_snap=utah_july_snap.drop(['State FIPS code','Name'],axis=1)
utah_july17_snap=utah_july_snap[['County FIPS code','July 2017']]
```

[35]:
```
# Modifu FIPS data for plotting
fips =list(utah_july17_snap['County FIPS code'])
fips_modified=[]
for i in fips:
    if (i <10):
        fips_modified.append(int('4900'+str(i)))
    else:
        fips_modified.append(int('490'+str(i)))
```

[40]:
```
# plot
values=list(utah_july17_snap['July 2017'])
fips =  fips_modified   #list(utah_july17_snap['County FIPS code'])
endpts = list(np.mgrid[min(values):max(values):8j])
colorscale = ["#030512","#1d1d3b","#323268","#3d4b94","#3e6ab0",
              "#4989bc","#60a7c7","#85c5d3","#b7e0e4","#eafcfd"]
fig = ff.create_choropleth(
    fips=fips, values=values, scope=['Utah'], show_state_data=True,
    colorscale=colorscale,
```

```
    binning_endpoints=endpts, round_legend_values=True,
   plot_bgcolor='rgb(229,229,229)',
   paper_bgcolor='rgb(229,229,229)',
    legend_title='County SNAP 2017 July',
    county_outline={'color': 'rgb(255,255,255)', 'width': 0.5},
   exponent_format=True,
)
fig.layout.template = None
fig.show()
```

Expected result. Very high number of foodstamp in SLC area follwed by immediate north and south. Most of the other counties are very low It suggests - population density proportionate to foodstamp numbers

External (census) data for the states

[570]:

```
# data Processing
country_pop=county_population[['state_name','pop1981', 'pop1982','pop1983',␣
↪'pop1984', 'pop1985',
             'pop1986', 'pop1987', 'pop1988','pop1989', 'pop1990', 'pop1991',␣
↪'pop1992', 'pop1993',
              'pop1994','pop1995', 'pop1996', 'pop1997', 'pop1998', 'pop1999',␣
↪'pop2000','pop2001',
             'pop2002', 'pop2003', 'pop2004', 'pop2005', 'pop2006','pop2007',␣
↪'pop2008', 'pop2009']]\
          ␣
↪[((county_population['state_name']=='Utah')&(county_population['areaname']=='Utah'))|\
               ␣
↪((county_population['state_name']=='Connecticut')&(county_population['areaname']=='Connecti
               ␣
↪(county_population['state_name']=='Mississippi')&(county_population['areaname']=='Mississip
country_pop=country_pop.rename(columns={col:int(col[3:]) for col in␣
↪list(country_pop.columns)\
                                        if col!='state_name'})
country_pop
```

[570]:

```
        state_name       1981       1982       1983       1984       1985  \
628    Connecticut  3128837.0  3139014.0  3162355.0  3180014.0  3201131.0
2833   Mississippi  2539032.0  2556776.0  2567719.0  2578053.0  2588103.0
5606          Utah  1515472.0  1558314.0  1594943.0  1622342.0  1642910.0

           1986       1987       1988       1989       1990       1991  \
628   3223741.0  3247290.0  3271954.0  3283404.0  3289056.0  3288640.0
2833  2593596.0  2588545.0  2580349.0  2574272.0  2577426.0  2591230.0
5606  1662833.0  1678120.0  1689372.0  1705865.0  1729722.0  1771941.0

           1992       1993       1994       1995       1996       1997  \
```

```
628   3274997.0  3272325.0  3268346.0  3265293.0  3267030.0  3268514.0
2833  2610193.0  2635574.0  2663450.0  2690788.0  2709925.0  2731826.0
5606  1821498.0  1875993.0  1930436.0  1976774.0  2022253.0  2065397.0

           1998       1999       2000       2001       2002       2003  \
628   3272563.0  3282031.0  3411726.0  3428433.0  3448382.0  3467673.0
2833  2751335.0  2768619.0  2848310.0  2853313.0  2858643.0  2867678.0
5606  2100562.0  2129836.0  2244314.0  2291250.0  2334473.0  2379938.0

           2004       2005       2006       2007       2008       2009
628   3474610.0  3477416.0  3485162.0  3488633.0  3502932.0  3518288.0
2833  2886006.0  2900116.0  2897150.0  2921723.0  2940212.0  2951996.0
5606  2438915.0  2499637.0  2583724.0  2663796.0  2727343.0  2784572.0
```

[586]:
```
# data processing another table
df_pop_2018=pop_est_2018[['Unnamed:␣
↪0',2010,2011,2012,2013,2014,2015,2016,2017,2018]]\
            [(pop_est_2018['Unnamed: 0']=='.Connecticut')|(pop_est_2018['Unnamed:
↪ 0']=='.Mississippi')|\
              (pop_est_2018['Unnamed: 0']=='.Utah')]
df_pop_2018=df_pop_2018.rename(columns={'Unnamed: 0':'state_name'})
df_pop_2018['state_name']=df_pop_2018['state_name'].apply(lambda x: x[1:])
df_pop_2018
```

[586]:
```
     state_name       2010       2011       2012       2013       2014  \
11  Connecticut  3579114.0  3588283.0  3594547.0  3594841.0  3594524.0
29  Mississippi  2970548.0  2978731.0  2983816.0  2988711.0  2990468.0
49         Utah  2775332.0  2814384.0  2853375.0  2897640.0  2936879.0

         2015       2016       2017       2018
11  3587122.0  3578141.0  3573297.0  3571520.0
29  2988471.0  2987938.0  2988510.0  2981020.0
49  2981835.0  3041868.0  3101042.0  3153550.0
```

[603]:
```
# merging data
df_pop=pd.merge(country_pop,df_pop_2018,on='state_name')
df_pop['state_name']=df_pop['state_name'].apply(lambda x: 'pop_'+str(x))
df_pop=df_pop.set_index(['state_name'])
df_pop=df_pop.T.reset_index()
df_pop=df_pop.rename(columns={'index':'Year'})
```

Statesnap data

[604]:
```
# get data
df_state_snap=statesnap[['Year','Num.␣
↪Month','Utah','Connecticut','Mississippi']][statesnap['Year']>1981.0]\
                        .sort_values(by=['Year','Num. Month'])
```

```
df_state_snap['Year']=df_state_snap['Year'].astype(int)
df_state_snap=df_state_snap.groupby('Year').agg({'Utah':'mean','Connecticut':
↪'mean','Mississippi':'mean'}).reset_index()
```

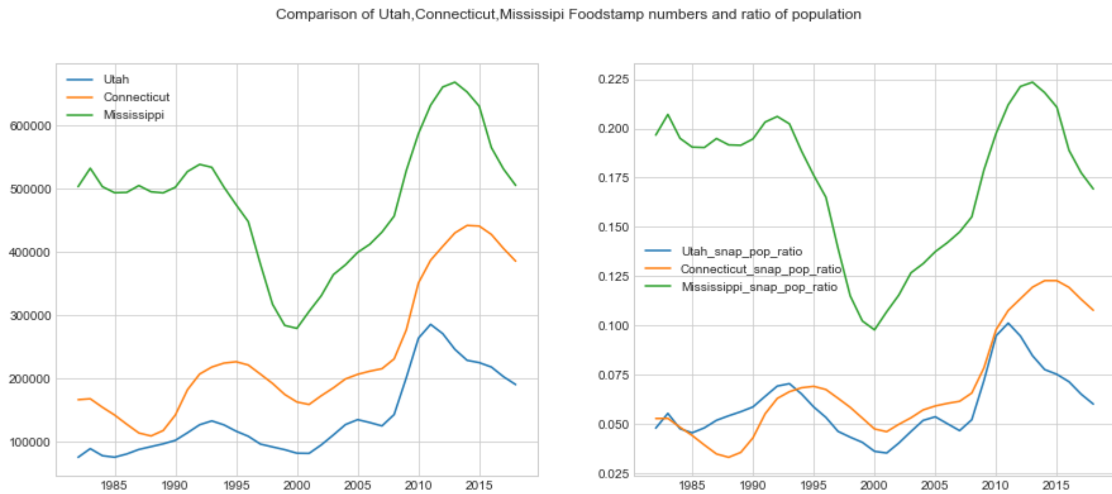
[607]:
```
df_state_snap=pd.merge(df_pop,df_state_snap,on=['Year'])
```

Ratio for snap to pop

[610]:
```
df_state_snap['Utah_snap_pop_ratio']=df_state_snap['Utah']/
↪df_state_snap['pop_Utah']
df_state_snap['Conecticut_snap_pop_ratio']=df_state_snap['Connecticut']/
↪df_state_snap['pop_Connecticut']
df_state_snap['Mississippi_snap_pop_ratio']=df_state_snap['Mississippi']/
↪df_state_snap['pop_Mississippi']
df_state_snap.columns
```

[610]:
```
Index(['Year', 'pop_Connecticut', 'pop_Mississippi', 'pop_Utah', 'Utah',
       'Connecticut', 'Mississippi', 'Utah_snap_pop_ratio',
       'Conecticut_snap_pop_ratio', 'Mississippi_snap_pop_ratio'],
      dtype='object')
```

[612]:
```
# Plot
fig, (ax1,ax2) = plt.subplots(1, 2,figsize=(15,6))
fig.suptitle('Comparison of Utah,Connecticut,Mississipi Foodstamp numbers and␣
↪ratio of population')

ax1.plot(df_state_snap['Year'],df_state_snap['Utah'],label='Utah')
ax1.plot(df_state_snap['Year'],df_state_snap['Connecticut'],label='Connecticut')
ax1.plot(df_state_snap['Year'],df_state_snap['Mississippi'],label='Mississippi')
ax1.legend()

ax2.
↪plot(df_state_snap['Year'],df_state_snap['Utah_snap_pop_ratio'],label='Utah_snap_pop_ratio'
ax2.
↪plot(df_state_snap['Year'],df_state_snap['Conecticut_snap_pop_ratio'],label='Connecticut_sn
ax2.
↪plot(df_state_snap['Year'],df_state_snap['Mississippi_snap_pop_ratio'],label='Mississippi_s

ax2.legend()

plt.show()
```



1) Overall decrease in foodstamp number after 2012 . 2) Utah and connecticut have similar patern but mississippi has different

Data preperation for modeling

Aggregating irs data and allpovu data

[371]:
```
df_agg_irs=irs[(irs['Year']>=1998)]
measure_list=['Total exemptions','Poor exemptions','Median AGI', 'Mean AGI']
# 'Age 65 and over exemptions','Age 65 and over poor exemptions',\
 #'Child exemptions','Poor child exemptions', 'Total exemptions under age 65',\
#'Poor exemptions under age 65',
df_agg_irs=df_agg_irs.groupby('Name').agg({k:['mean','std'] for k in␣
↪measure_list})
df_agg_irs.columns=[str(col[0])+'_'+str(col[1]) for col in df_agg_irs]
df_agg_irs=df_agg_irs.reset_index()
```

[384]:
```
df_agg_irs.shape
```

[384]: (51, 9)

[352]:
```
dict_agg_allpovu={}
for state in irs_state:
    df=get_allpovu_by_state(state)
    dict_agg_allpovu[state]=[df['povu_all_ages'].mean(),df.loc[:
↪,'povu_all_ages'].std(),df['povu_5_17'].mean(),\
                            df.loc[:,'povu_5_17'].std(),df['povu_0_4'].mean(),df.loc[:
↪,'povu_0_4'].std()]
df_agg_allpovu=pd.DataFrame(dict_agg_allpovu).T.reset_index()
```

```
df_agg_allpovu.
↪columns=['Name','povu_all_ages_mean','povu_all_ages_std','povu_5_17_mean',
                          'povu_5_17_std','povu_0_4_std','povu_0_4_std']
df_agg_allpovu.columns=[str(col[0])+'_'+str(col[1]) for col in df_agg_allpovu]
df_agg_allpovu=df_agg_allpovu.reset_index()
```

[385]:
```
df_agg=pd.merge(df_agg_irs,df_agg_irs,on=['Name'])
df_agg=df_agg.set_index(['Name'])
df_agg_array=np.array(df_agg)
df_agg_array.shape
```

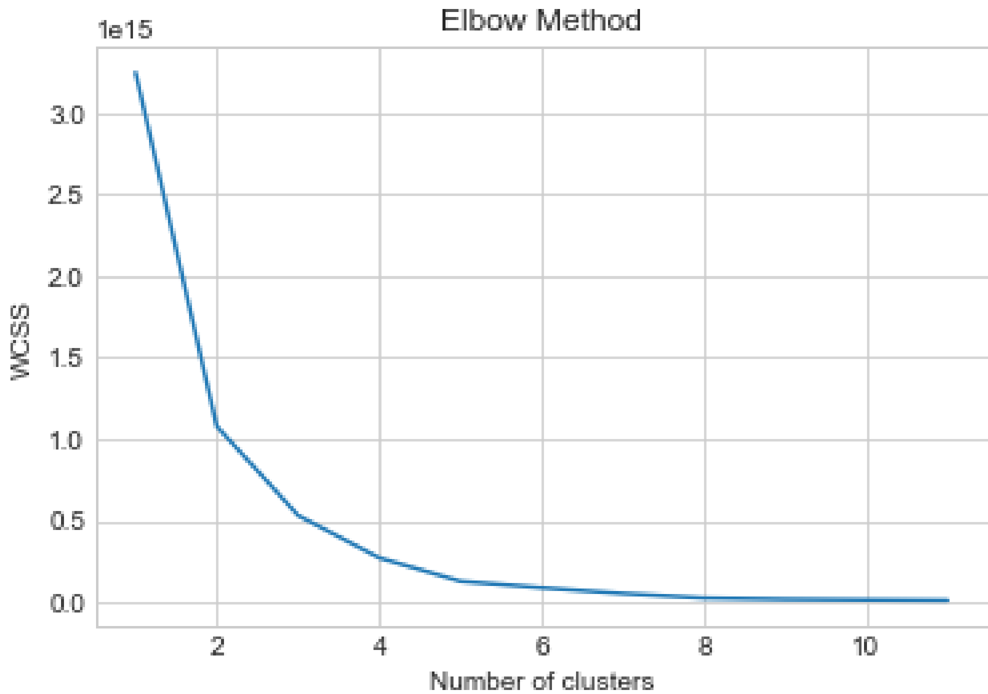
[385]:
```
(51, 16)
```

[386]:
```
from sklearn import preprocessing
min_max_scaler = preprocessing.MinMaxScaler()
df_agg_array_scaled = min_max_scaler.fit_transform(df_agg_array)
```

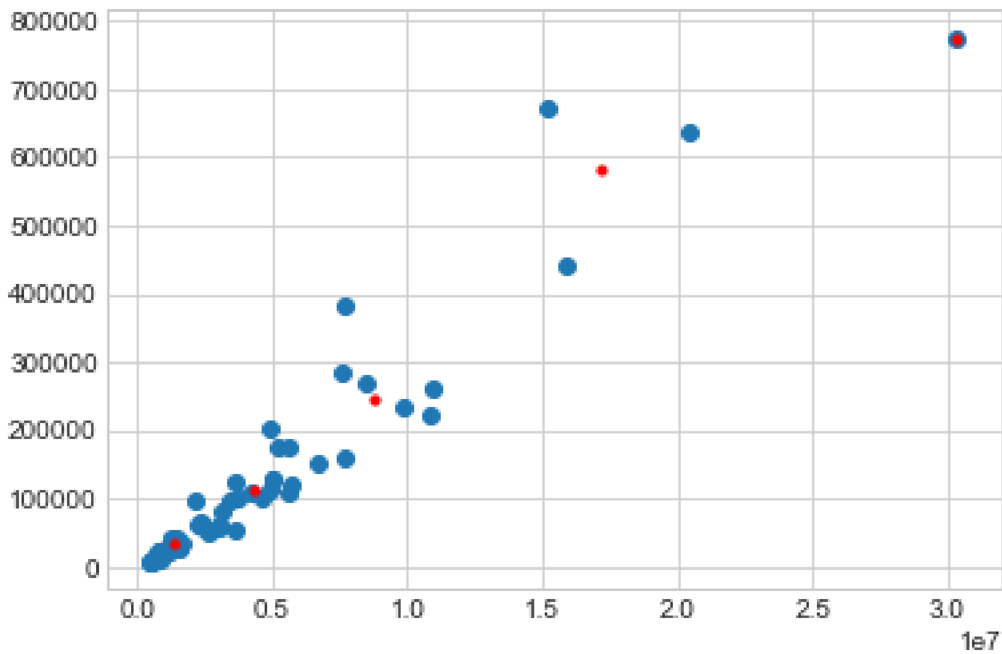
K-mean clustering - cluster states with similar patterns

[374]:
```
from sklearn.cluster import KMeans
```

[387]:
```
wcss = []
for i in range(1, 12):
    kmeans = KMeans(n_clusters=i, init='k-means++', max_iter=1200, n_init=10,␣
↪random_state=0)
    kmeans.fit(df_agg_array)
    wcss.append(kmeans.inertia_)
plt.plot(range(1, 12), wcss)
plt.title('Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()
```



[393]:
```
kmeans = KMeans(n_clusters=5, init='k-means++', max_iter=300, n_init=10,␣
↪random_state=0)
pred_y = kmeans.fit_predict(df_agg_array)
plt.scatter(df_agg_array[:,0], df_agg_array[:,3])
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:,3], s=10,␣
↪c='red')
plt.show()
```



Clusters are not well seperated. Not very useful information we can get from here but there are some outliers

Regression model

To find relation with number of foodstamp with other feature variables

[401]:
```
df_statesnap=statesnap[statesnap['Year']>=1998]
df_statesnap=df_statesnap.drop(['Month', 'Num. Month'],axis=1)
```

[403]:
```
df_agg=df_statesnap.groupby('Year').mean().reset_index()
```

Target variable

[474]:
```
target=[]
for yr in list(df_agg['Year'].astype(int).unique()):
    for state in list(set(df_agg.columns)-{'Year'}):
        target.append({"State":state,"Year":yr,"Target":
 ↪round(df_agg[state][df_agg['Year']==yr].values[0],0)})

target=pd.DataFrame(target)
target['Year']=target['Year'].astype(int)
#target=target.set_index(['State','Year'])
#target
```

[479]:
```
target.shape
```

[479]:
```
(1071, 3)
```

Prepare feature variables

[459]:
```
df_agg_irs=irs[(irs['Year']>=1998)]
measure_list=['Total exemptions','Poor exemptions','Median AGI', 'Mean AGI',␣
 ↪'Age 65 and over exemptions',\
              'Age 65 and over poor exemptions','Child exemptions','Poor child␣
 ↪exemptions',\
              'Total exemptions under age 65','Poor exemptions under age 65']
df_agg_irs=df_agg_irs.groupby(['Name','Year']).agg({k:['mean'] for k in␣
 ↪measure_list})
df_agg_irs.columns=[str(col[0])+'_'+str(col[1]) for col in df_agg_irs]
df_agg_irs=df_agg_irs.reset_index()
df_agg_irs=df_agg_irs.rename(columns={'Name':'State'})
```

[460]:
```
df_agg_allpovu=[]
for state in irs_state:
    df=get_allpovu_by_state(state)
    for yr in list(df['Year'].unique()):
        df_agg_allpovu.append({"State":state,"Year":yr,"all_ages":
 ↪df['povu_all_ages'][df['Year']==yr].values[0],
                        "5-17":df['povu_5_17'][df['Year']==yr].values[0],"0_4":
 ↪df['povu_0_4'][df['Year']==yr].values[0]})
df_agg_allpovu=pd.DataFrame(df_agg_allpovu)
```

[484]:
```
df_final=pd.merge(df_agg_allpovu,df_agg_irs,on=['State','Year'])
df_final=pd.merge(df_final,target,on=['State','Year'])
df_final.head()
```

[484]:
```
     State  Year    all_ages       5-17        0_4  Total exemptions_mean  \
0  Florida  1998  15690191.0  2577387.0   942071.0               12400211
1  Florida  1999  16002039.0  2656195.0   994725.0               13016199
2  Florida  2000  16306747.0  2730693.0  1011506.0               13346772
3  Florida  2001  16684871.0  2799200.0  1045990.0               13658964
4  Florida  2002  17028820.0  2842050.0  1069849.0               13908972

   Poor exemptions_mean  Median AGI_mean  Mean AGI_mean  \
0               2100290            24684          42456
1               2144439            25852          47530
2               2184709            27032          50605
3               2324292            27111          48192
4               2456427            27028          47560
```

```
   Age 65 and over exemptions_mean  Age 65 and over poor exemptions_mean  \
0                          1529947                                147165
1                          1585790                                157091
2                          1603783                                158912
3                          1646293                                195736
4                          1657158                                235664

   Child exemptions_mean  Poor child exemptions_mean  \
0                3589248                      801283
1                3775846                      804422
2                3879690                      816691
3                3968316                      846756
4                4070027                      881126

   Total exemptions under age 65_mean  Poor exemptions under age 65_mean  \
0                            10870264                            1953125
1                            11430409                            1987348
2                            11742989                            2025797
3                            12012671                            2128556
4                            12251814                            2220763

      Target
0   964450.0
1   920645.0
2   876052.0
3   909955.0
4  1009809.0
```

[485]:
```
df_final.shape
```

[485]: (1020, 16)

[486]:
```
from sklearn import preprocessing
from sklearn.model_selection import KFold, StratifiedKFold,train_test_split
df_final=df_final.set_index(['State','Year'])
indices=df_final.index.values
labels = np.array(df_final['Target'])
features= df_final.drop(['Target'], axis = 1)
features = np.array(features)
min_max_scaler = preprocessing.MinMaxScaler()
features_scaled = min_max_scaler.fit_transform(features)
train_features, eval_features, train_labels, eval_labels,idx_train,idx_eval = \
            train_test_split(features_scaled, labels,indices, test_size = 0.2,␣
 ↪random_state = 7)
```

Decision tree regression

```
[513]: from sklearn.tree import DecisionTreeRegressor
from sklearn import metrics
from sklearn import tree
regressor = DecisionTreeRegressor(criterion='mse', max_depth=8,␣
 ↪max_features=None,
                          max_leaf_nodes=None, min_impurity_decrease=0.0,
                          min_impurity_split=None, min_samples_leaf=1,
                          min_samples_split=2, min_weight_fraction_leaf=0.0,
                          presort=False, random_state=None, splitter='best')
regressor.fit(train_features,train_labels)
```

```
[513]: DecisionTreeRegressor(criterion='mse', max_depth=8, max_features=None,
                          max_leaf_nodes=None, min_impurity_decrease=0.0,
                          min_impurity_split=None, min_samples_leaf=1,
                          min_samples_split=2, min_weight_fraction_leaf=0.0,
                          presort=False, random_state=None, splitter='best')
```

```
[514]: def mean_absolute_percentage_error(y_true, y_pred):
    y_true, y_pred = np.array(y_true), np.array(y_pred)
    return np.mean(np.abs((y_true - y_pred) / y_true)) * 100
```

```
[515]: eval_pred = regressor.predict(eval_features)
print('r squared error  :'+str(metrics.r2_score(eval_labels,eval_pred)))
print('mean absolute percentage error :
 ↪'+str(mean_absolute_percentage_error(eval_labels,eval_pred)))
```

```
r squared error  :0.9431421590022836
mean absolute percentage error :20.117916553484356
```

```
[519]: regressor.feature_importances_
```

```
[519]: array([0.04325677, 0.00162446, 0.01589624, 0.01378029, 0.74711845,
       0.00457945, 0.00796651, 0.00322749, 0.12899392, 0.00145034,
       0.02288654, 0.00083801, 0.00838154])
```

```
[518]: df_top_feature_importance=pd.DataFrame(zip(df_final.columns,regressor.
 ↪feature_importances_),\
                                       columns=['features','importance'])
df_top_feature_importance.sort_values(by='importance',ascending=False).head(5)
```

[518]:

	features	importance
4	Poor exemptions_mean	0.747118
8	Age 65 and over poor exemptions_mean	0.128994
0	all_ages	0.043257
10	Poor child exemptions_mean	0.022887
2	0_4	0.015896

1) With very simple modeling and without any hyperparameter tuning we can see good relation

between number of foodstamp users and other economic variables. 2) ‘Poor Exemption’ is very strongly related to target variable. 3) This model can be improved more to predict number of foodstamp users for each state each year or month 4) For future prediction,feature variable data can be estimated by timeseries analysis

Conclusion Here the analysis is done in very high level This dataset is really reach and lot of good economic analysis can be done using this data. This analysis can be very helpful to understad relation between economy, poverty and how society changing Many special analyis -for example 2010-12 financial crisis and impact can be analysed