Capstone-AdaReg

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1 Prediction of United States' Counties Poverty Rates

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1.1 Executive Summary

This document presents the results of the regression analysis to predict poverty rates of United States' Counties. The result of this regression analysis is the creation of an AdaBoostRegressor. This AdaBoostRegressor is able to predict United States' Counties poverty rates with an RMSE of 2.7853.

In the data understanding phase was discovered that the following features play a significant role in predicting United States' counties poverty rates. They have moderate positive and negative Pearson correlation coefficients. Furthermore the Boxplots show enough variation and separation of the data with respect to the target variable poverty_rate. However recursive function elimination was ultimately used to select the optimum number of features for the lowest RMSE score.

Significant Features	Short Description
area__rucc	Rural urban continuum code of county
econ__economic_typology	economic dependence type of county
aui_pct65y_cat	created categorical feature combining 'area__urban_influence' and categorical percentage of 65 years old per county

Significant Features	Short Description
demo__pct_adults_less_than_a_high_school_diploma	percentage of adults with less than high school diploma per county
health__homicides_per_100k	homicides per 100k inhabitants per county
econ__pct_unemployment	percentage of unemployment per county
health__pct_low_birthweight	percentage of low birth weight per county
econ__pct_uninsured_adults	percentage of uninsured adults per county
health__pct_diabetes	percentage of diabetes per county
demo__pct_non_hispanic_african_american	percentage of African Americans per county
econ__pct_civilian_labor	percentage of civilian labor per county

The CRISP-DM Methodology was used in order to create an accurate regression model:

- **Business Understanding**: read through the 'Rural Poverty & Well-being' report to better understand the circumstances of poverty.
- **Data Understanding**: explore the quantitative and categorical variables that play a key role in predicting poverty rates. Create new, better and informative features.
- **Data Preparation**: drop redundant and uninformative features, fill missing values, etc.
- **Modeling**: create and select the best regression model.
- **Evaluation**: evaluate the regression models using nested cross validation.
- **Deployment**: the deployment of the regression model is not strictly applicable here. However presenting the results of the regression analysis with this report can be considered as the deployment step.

1.2 Business Understanding

As described in the online report the 'Rural Poverty & Well-being': "Concentrated poverty contributes to poor housing and health conditions, higher crime and school dropout rates, as well as employment dislocations". With this information the data will be explored to see how health, crime,education and employment related factors contribute to poverty.

Another important feature of poverty is time. An area that doesn't have a high level of poverty in two following years is likely better off than an area that has a high level of poverty in both years. It will not be possible to construct a feature with this information because we cannot compare the state's poverty rate over year 'a' and 'b' within this data set. We don't have a unique key to identify counties.

Counties are generally compared by their Non-Metro and Metro status. There is more poverty in Non-Metro areas than Metro areas. Poverty is also higher under certain ages and ethnicities. Here also the data will be explored on the basis of this information.

```
In [253]: import re
          import bs4
          import time
          import plyfile
          import html5lib
          import multiprocessing
          import itertools

          import numpy as np
          import pandas as pd

          import seaborn as sns
          from scipy import misc
          import scipy.io.wavfile as wavfile

          import scipy
          from math import sqrt
          from scipy import stats
          from pprint import pprint
          from sklearn import tree
          from sklearn.svm import SVC
          from sklearn import manifold
          from tempfile import mkdtemp
          from textwrap import wrap
          from matplotlib import cm as cm

          import sklearn.metrics as metrics
          from pandas.plotting import scatter_matrix
          from scipy.stats import randint as sp_randint
          from sklearn.pipeline import TransformerMixin
          from sklearn.metrics.scorer import make_scorer
          from sklearn.pipeline import Pipeline
          from sklearn.decomposition import PCA
```

```python
from sklearn.datasets import load_iris
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import Binarizer
from sklearn.naive_bayes import MultinomialNB
from sklearn.tree import DecisionTreeRegressor, DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.feature_selection import RFECV, SelectFromModel, f_regression, SelectKBe
from sklearn.ensemble import RandomForestClassifier, AdaBoostRegressor, AdaBoostClas
from sklearn.dummy import DummyClassifier, DummyRegressor
from sklearn.cluster import AgglomerativeClustering, KMeans
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.linear_model import LinearRegression, LassoCV, RidgeCV, Lasso, Ridge
from sklearn.preprocessing import MaxAbsScaler, MinMaxScaler, Normalizer, RobustScale
from sklearn.metrics import recall_score, accuracy_score, confusion_matrix, roc_curve
from sklearn.model_selection import train_test_split, GridSearchCV, RandomizedSearch(

import matplotlib
import matplotlib.pyplot as plt
from matplotlib import cm as cm
from mpl_toolkits.mplot3d import Axes3D
from pandas.plotting import parallel_coordinates, andrews_curves

%matplotlib inline
matplotlib.style.use('ggplot')

pd.set_option('display.max_columns', None)
```

1.3 Data Understanding

In order to build this regression model and determine its most significant features a thorough data exploration was done to understand the relationship between poverty rates and other features. ### Initial Data Exploration The dataset consists of 3198 records about United States' counties. Each record contains socioeconomic indicators about a United States' county for a given year. Besides the 'row_id', 'yr' and the target value 'poverty_rate', the dataset contains 32 features about socioeconomic indicators.

```python
In [194]: poverty_train = pd.read_csv('./Microsoft_-_DAT102x_Predicting_Poverty_in_the_United_S
```

```python
In [195]: train_shape_tmp = poverty_train.shape
```

```python
In [196]: train_dytpes_tmp = poverty_train.dtypes
```

Individual Feature Statistics Here are the summary statistics for all the socioeconomic features: - summary statistics of categorical variables: the total count (count), number of unique elements (unique), most frequent element (top) and the frequency of the most frequent element (frequent) - summary statistics of quantitative variables: the mean, the standard deviation (std), the minimum value (min), 25% percentile, 50% percentile (median), 75% percentile and the maximum value (max).

In [254]: poverty_train.drop(columns=['row_id'], axis=1).describe(include='all').T

Out[254]:

```
                                               count unique  \
area__rucc                                      3198      9
area__urban_influence                           3198     12
econ__economic_typology                         3198      6
econ__pct_civilian_labor                        3198    NaN
econ__pct_unemployment                          3198    NaN
econ__pct_uninsured_adults                      3196    NaN
econ__pct_uninsured_children                    3196    NaN
demo__pct_female                                3196    NaN
demo__pct_below_18_years_of_age                 3196    NaN
demo__pct_aged_65_years_and_older               3196    NaN
demo__pct_hispanic                              3196    NaN
demo__pct_non_hispanic_african_american         3196    NaN
demo__pct_non_hispanic_white                    3196    NaN
demo__pct_american_indian_or_alaskan_native     3196    NaN
demo__pct_asian                                 3196    NaN
demo__pct_adults_less_than_a_high_school_diploma 3198    NaN
demo__pct_adults_with_high_school_diploma       3198    NaN
demo__pct_adults_with_some_college              3198    NaN
demo__pct_adults_bachelors_or_higher            3198    NaN
demo__birth_rate_per_1k                         3198    NaN
demo__death_rate_per_1k                         3198    NaN
health__pct_adult_obesity                       3196    NaN
health__pct_adult_smoking                       2734    NaN
health__pct_diabetes                            3196    NaN
health__pct_low_birthweight                     3016    NaN
health__pct_excessive_drinking                  2220    NaN
health__pct_physical_inacticity                 3196    NaN
health__air_pollution_particulate_matter        3170    NaN
health__homicides_per_100k                      1231    NaN
health__motor_vehicle_crash_deaths_per_100k     2781    NaN
health__pop_per_dentist                         2954    NaN
health__pop_per_primary_care_physician          2968    NaN
yr                                              3198      2


area__rucc                                      Nonmetro - Urban population of 2,5
area__urban_influence                           Small-in a metro area with fewer t
econ__economic_typology
econ__pct_civilian_labor
econ__pct_unemployment
econ__pct_uninsured_adults
econ__pct_uninsured_children
demo__pct_female
demo__pct_below_18_years_of_age
demo__pct_aged_65_years_and_older
```

```
demo__pct_hispanic
demo__pct_non_hispanic_african_american
demo__pct_non_hispanic_white
demo__pct_american_indian_or_alaskan_native
demo__pct_asian
demo__pct_adults_less_than_a_high_school_diploma
demo__pct_adults_with_high_school_diploma
demo__pct_adults_with_some_college
demo__pct_adults_bachelors_or_higher
demo__birth_rate_per_1k
demo__death_rate_per_1k
health__pct_adult_obesity
health__pct_adult_smoking
health__pct_diabetes
health__pct_low_birthweight
health__pct_excessive_drinking
health__pct_physical_inacticity
health__air_pollution_particulate_matter
health__homicides_per_100k
health__motor_vehicle_crash_deaths_per_100k
health__pop_per_dentist
health__pop_per_primary_care_physician
yr

                                                  freq       mean        std  \
area__rucc                                         608        NaN        NaN
area__urban_influence                              692        NaN        NaN
econ__economic_typology                           1266        NaN        NaN
econ__pct_civilian_labor                           NaN   0.467071   0.074541
econ__pct_unemployment                             NaN  0.0596104  0.0228497
econ__pct_uninsured_adults                         NaN   0.217534  0.0673718
econ__pct_uninsured_children                       NaN  0.0859202  0.0400046
demo__pct_female                                   NaN   0.498781  0.0242508
demo__pct_below_18_years_of_age                    NaN   0.227763  0.0342909
demo__pct_aged_65_years_and_older                  NaN   0.170137  0.0435937
demo__pct_hispanic                                 NaN  0.0902334   0.142707
demo__pct_non_hispanic_african_american            NaN  0.0911167   0.147104
demo__pct_non_hispanic_white                       NaN   0.770207   0.207903
demo__pct_american_indian_or_alaskan_native        NaN  0.0246586  0.0846341
demo__pct_asian                                    NaN  0.0133035  0.0253656
demo__pct_adults_less_than_a_high_school_diploma   NaN   0.148794  0.0682547
demo__pct_adults_with_high_school_diploma          NaN     0.3503  0.0705342
demo__pct_adults_with_some_college                 NaN   0.301366  0.0524976
demo__pct_adults_bachelors_or_higher               NaN    0.19954  0.0891577
demo__birth_rate_per_1k                            NaN     11.677    2.73952
demo__death_rate_per_1k                            NaN    10.3011    2.78614
health__pct_adult_obesity                          NaN   0.307599   0.043404
health__pct_adult_smoking                          NaN   0.213519  0.0630903
```

health__pct_diabetes	NaN	0.109287	0.0231967
health__pct_low_birthweight	NaN	0.0835345	0.0223822
health__pct_excessive_drinking	NaN	0.164832	0.0502321
health__pct_physical_inacticity	NaN	0.277309	0.0529475
health__air_pollution_particulate_matter	NaN	11.6265	1.54493
health__homicides_per_100k	NaN	5.95075	5.06337
health__motor_vehicle_crash_deaths_per_100k	NaN	21.1161	10.517
health__pop_per_dentist	NaN	3431.44	2569.44
health__pop_per_primary_care_physician	NaN	2551.35	2100.48
yr	1599	NaN	NaN

	min	25%	\
area__rucc	NaN	NaN	
area__urban_influence	NaN	NaN	
econ__economic_typology	NaN	NaN	
econ__pct_civilian_labor	0.217	0.42	
econ__pct_unemployment	0.008	0.044	
econ__pct_uninsured_adults	0.046	0.166	
econ__pct_uninsured_children	0.009	0.057	
demo__pct_female	0.294	0.493	
demo__pct_below_18_years_of_age	0.098	0.207	
demo__pct_aged_65_years_and_older	0.043	0.142	
demo__pct_hispanic	0	0.019	
demo__pct_non_hispanic_african_american	0	0.006	
demo__pct_non_hispanic_white	0.06	0.648	
demo__pct_american_indian_or_alaskan_native	0	0.002	
demo__pct_asian	0	0.003	
demo__pct_adults_less_than_a_high_school_diploma	0.016129	0.0974683	
demo__pct_adults_with_high_school_diploma	0.0728205	0.305915	
demo__pct_adults_with_some_college	0.112821	0.265362	
demo__pct_adults_bachelors_or_higher	0.013986	0.13884	
demo__birth_rate_per_1k	4	10	
demo__death_rate_per_1k	0	8	
health__pct_adult_obesity	0.14	0.284	
health__pct_adult_smoking	0.05	0.171	
health__pct_diabetes	0.033	0.094	
health__pct_low_birthweight	0.025	0.068	
health__pct_excessive_drinking	0.038	0.129	
health__pct_physical_inacticity	0.097	0.243	
health__air_pollution_particulate_matter	7	10	
health__homicides_per_100k	-0.39	2.66	
health__motor_vehicle_crash_deaths_per_100k	3.09	13.46	
health__pop_per_dentist	339	1812.25	
health__pop_per_primary_care_physician	189	1419	
yr	NaN	NaN	

	50%	75%	max
area__rucc	NaN	NaN	NaN

```
area__urban_influence                                    NaN       NaN       NaN
econ__economic_typology                                  NaN       NaN       NaN
econ__pct_civilian_labor                               0.467     0.514         1
econ__pct_unemployment                                 0.057     0.071      0.24
econ__pct_uninsured_adults                             0.216     0.262     0.495
econ__pct_uninsured_children                           0.077     0.105     0.285
demo__pct_female                                       0.503     0.512     0.576
demo__pct_below_18_years_of_age                        0.226   0.24525     0.417
demo__pct_aged_65_years_and_older                      0.167     0.194     0.355
demo__pct_hispanic                                     0.035     0.088     0.945
demo__pct_non_hispanic_african_american                0.022   0.09625     0.855
demo__pct_non_hispanic_white                           0.854     0.936     0.998
demo__pct_american_indian_or_alaskan_native            0.007     0.014     0.852
demo__pct_asian                                        0.007     0.013     0.346
demo__pct_adults_less_than_a_high_school_diploma    0.133501  0.195171  0.466867
demo__pct_adults_with_high_school_diploma           0.355701  0.399197  0.551689
demo__pct_adults_with_some_college                  0.301595  0.335972  0.474216
demo__pct_adults_bachelors_or_higher                0.177247  0.233258  0.794872
demo__birth_rate_per_1k                                   11        13        29
demo__death_rate_per_1k                                   10        12        27
health__pct_adult_obesity                              0.309     0.334     0.484
health__pct_adult_smoking                              0.211   0.24975     0.526
health__pct_diabetes                                   0.109     0.124     0.197
health__pct_low_birthweight                             0.08     0.095     0.232
health__pct_excessive_drinking                         0.164     0.196     0.358
health__pct_physical_inacticity                         0.28     0.313     0.443
health__air_pollution_particulate_matter                  12        13        15
health__homicides_per_100k                              4.84     7.825     51.49
health__motor_vehicle_crash_deaths_per_100k            19.63     26.47    110.45
health__pop_per_dentist                                 2690   4089.75     28129
health__pop_per_primary_care_physician                  1999      2859     23400
yr                                                       NaN       NaN       NaN
```

In [198]:
```
poverty_labels = pd.read_csv('Microsoft_-_DAT102x_Predicting_Poverty_in_the_United_S
```

In [199]:
```
lbl_shape_tmp = poverty_labels.shape
```

In [200]:
```
lbl_dtype_tmp = poverty_labels.dtypes
```

Here are the summary statistics for the target variable which is quantitative:

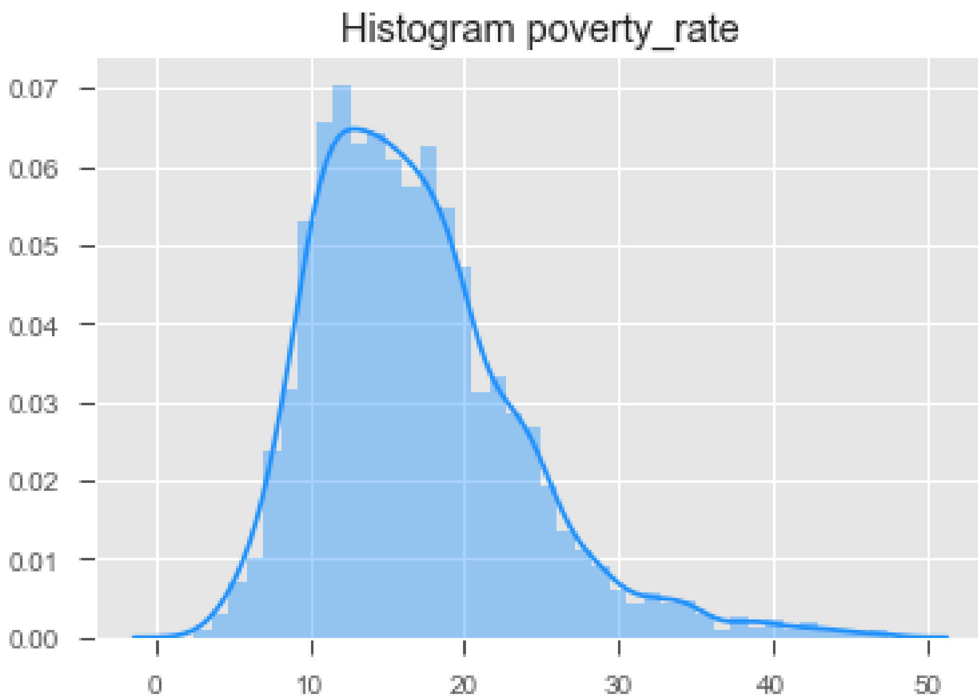
In [201]:
```
poverty_labels.drop(columns=['row_id'], axis=1).describe()
```

Out[201]:
```
       poverty_rate
count   3198.000000
mean      16.817136
std        6.697969
min        2.500000
25%       12.000000
```

```
50%        15.800000
75%        20.300000
max        47.400000
```

Poverty rates are right or positively skewed with a skew value of 1.048357. We can recognize a slight bell curve in the data. The mean and median are relatively close to each other and the standard deviation is relatively low which indicates low variability in the poverty rates. Most United States' counties have a poverty_rate between 10% and 20% poverty.

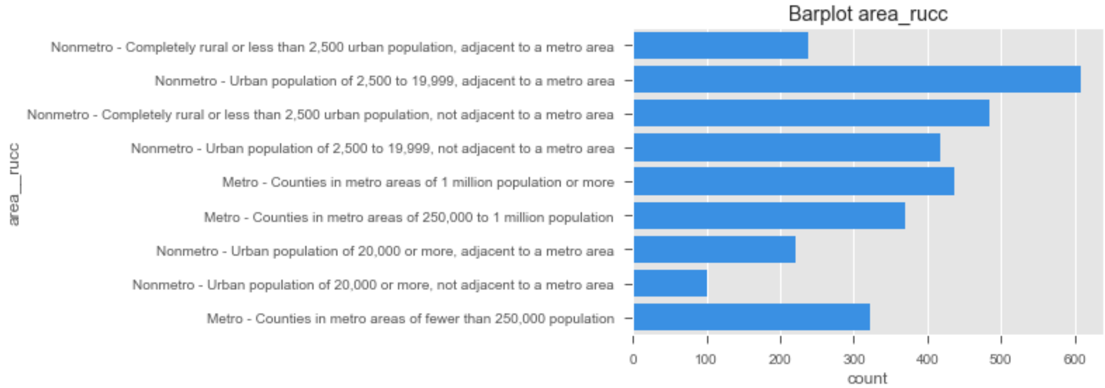
```
In [202]: ht_pov = sns.distplot(poverty_labels.drop(columns=['row_id'], axis=1), color='dodgerl
```



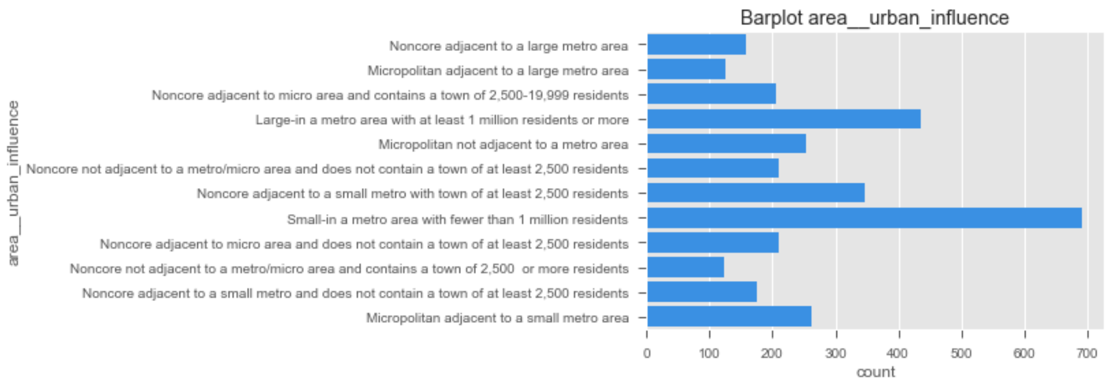

```
In [203]: poverty = pd.merge(poverty_train, poverty_labels, on='row_id')
          pov_shape_tmp = poverty.shape
```

From the summary statistics above, should be clear that there are three categorical variables included in the dataset: - area__rucc with 9 values: - 'Nonmetro - Urban population of 2,500 to 19,999, adjacent to a metro area' counties are most frequent with 608 counties. - 'Nonmetro - Urban population of 20,000 or more, not adjacent to a metro area' counties are most infrequent with 100 counties. - area__urban_influence with 12 values: - 'Small-in a metro area with fewer than 1 million residents' counties are most frequent with 692 counties. - 'Noncore not adjacent to a metro/micro area and contains a town of 2,500 or more residents' counties are most infrequent with 122. - econ__economic_typology with 6 values: - 'Non specialized' economic typology counties are most frequent with 1266 counties. - 'Mining-dependent' economic typology counties are most infrequent with 254 counties.

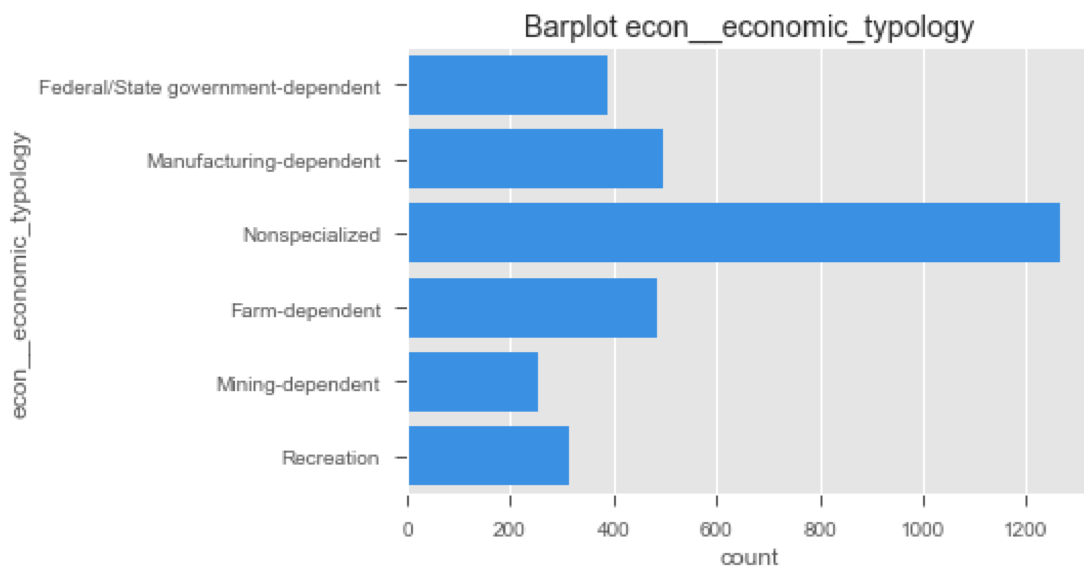
```
In [204]: bh_ar = sns.countplot(y='area__rucc', data=poverty, color='dodgerblue').set_title("Ba
```




```
In [205]: bh_aui = sns.countplot(y='area__urban_influence', data=poverty, color='dodgerblue').s
```




```
In [206]: bh_eet = sns.countplot(y='econ__economic_typology', data=poverty, color='dodgerblue')
```



1.3.1 Data Exploration and Visualization of Categorical Variables

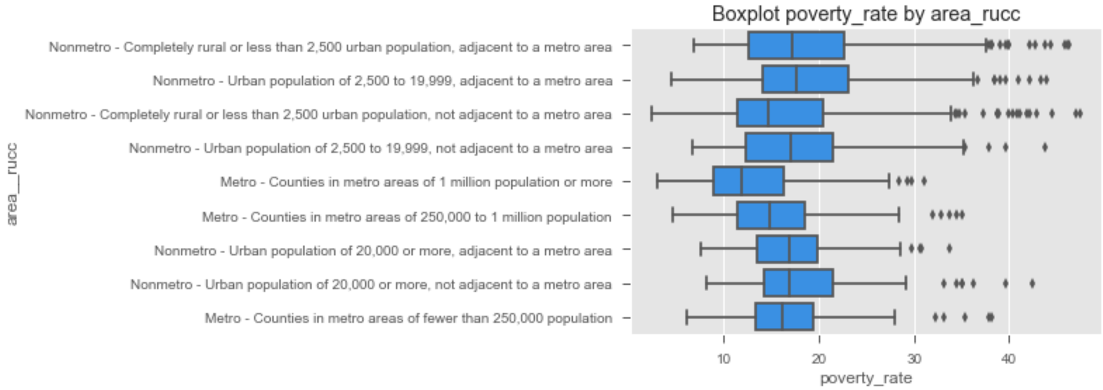
Here the predictive value of the categorical variables 'econ__economic_typology', 'area__urban_influence', 'area__rucc' and 'yr' is explored. Box plots are used to explore these categorical variables.

The boxplots of the categorical variables "econ__economic_typology", "area__urban_influence" and "area__rucc" show interesting variation: * 'Farm-dependent' counties have the lowest poverty rates and 'Federal/State government-dependent' counties have the highest poverty rates. * 'Large-in a metro area with at least 1 million residents or more' counties have the lowest poverty rates. * 'Metro - Counties in metro areas with 1 million population or more' counties have the lowest poverty rates.

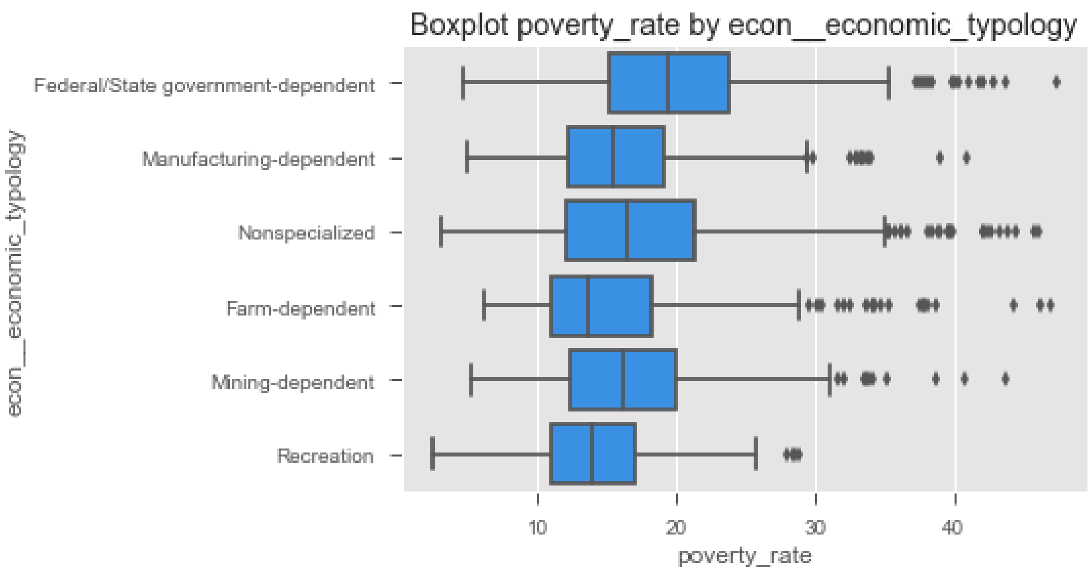
Furthermore by combining features more interesting categorical variables can be created explaining much more of the variance in poverty rates. * "demo__pct_aged_65_years_and_older" and "area__urban_influence". The general trend is that counties with a low percentage population of "65 years or older" have a higher poverty rate.

The difference in poverty over year 'a' and 'b' is really minimal. Furthermore it doesn't make sense to use this feature to predict poverty rates. This feature will be dropped at the cleaning stage.

```
In [207]: bpd_ar = sns.boxplot(orient="h", x='poverty_rate', y='area__rucc', data=poverty, col
```

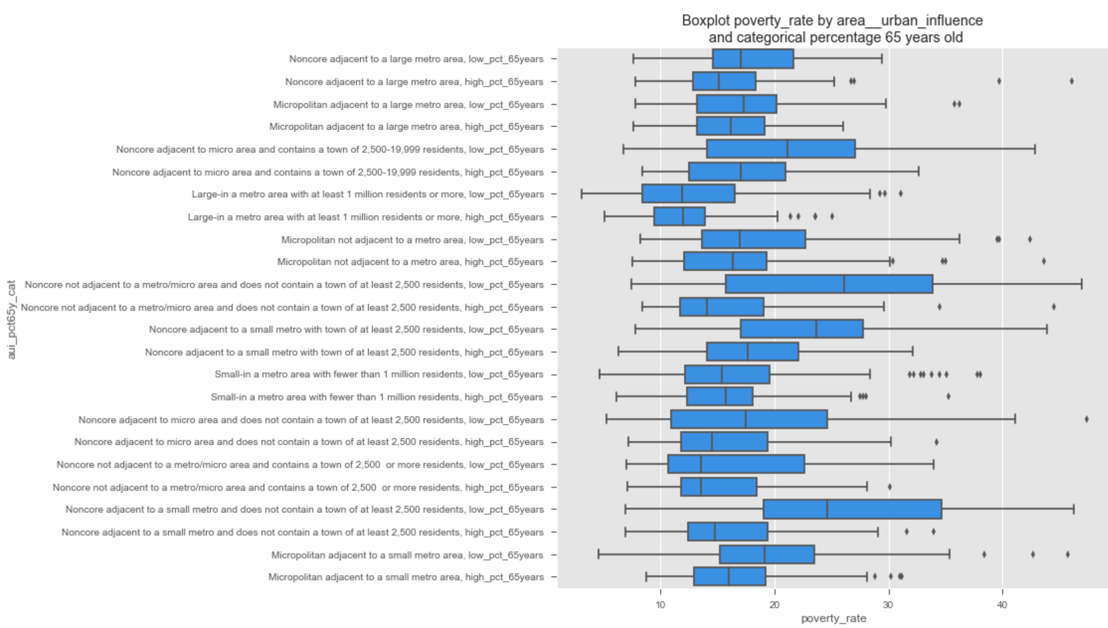



```
In [208]: bpd_eet = sns.boxplot(orient="h", x='poverty_rate', y='econ__economic_typology', data
```




```
In [209]: def create_old_age_cat(input_df):
              low_pct_olds = poverty.demo__pct_aged_65_years_and_older < 0.167000
              high_pct_olds = poverty.demo__pct_aged_65_years_and_older >= 0.167000
              input_df.loc[low_pct_olds,'pct_65years_cat'] = 'low_pct_65years'
              input_df.loc[high_pct_olds,'pct_65years_cat'] = 'high_pct_65years'

              age_old_cats = ['low_pct_65years','high_pct_65years']
              input_df.loc[:,'pct_65years_cat'] = input_df.pct_65years_cat.astype('category')
              input_df.loc[:,'pct_65years_cat'] = input_df.pct_65years_cat.cat.set_categories(a
              return input_df

In [210]: poverty = create_old_age_cat(poverty)
```

```
In [211]: def create_aui_pct65y_cat(input_df):
              aui_cats = input_df.area__urban_influence.unique()
              pct65y_cats = input_df.pct_65years_cat.cat.categories

              aui_pct65y_masks = [ ((input_df.area__urban_influence == aui) & (input_df.pct_65y
                                      , aui + ', ' + pct65y)
                                    for (aui, pct65y) in list(itertools.product(aui_cats, pct65y_

              aui_pct65y_lbls = [aui + ', ' + pct65y for (aui, pct65y)
                                 in list(itertools.product(aui_cats, pct65y_cats))]

              for mask, aui_pct65y_lb in aui_pct65y_masks:
                  input_df.loc[mask, 'aui_pct65y_cat'] = aui_pct65y_lb

              input_df.loc[:,'aui_pct65y_cat'] = input_df.aui_pct65y_cat.astype('category')
              input_df.loc[:,'aui_pct65y_cat'] = input_df.aui_pct65y_cat.cat.set_categories(aui
              return input_df

In [212]: poverty = create_aui_pct65y_cat(poverty)
          plt.figure(figsize=(10,10))
          bpd_eet = sns.boxplot(orient="h", x='poverty_rate', y='aui_pct65y_cat', data=poverty
```



1.3.2 Data Exploration and Visualization of Quantitative Variables

For the quantitative variables the correlation matrix is computed first followed by the visual display of the scatter plot matrices.

Correlation Matrix The strongest correlations observed are moderate positive and negative for the following features: - demo__pct_adults_less_than_a_high_school_diploma
- health__homicides_per_100k
- econ__pct_unemployment
- health__pct_low_birthweight
- econ__pct_uninsured_adults
- health__pct_diabetes
- demo__pct_non_hispanic_african_american
- econ__pct_civilian_labor

The whole correlation matrix of interest is shown here under.

Features	Pearson Correlation Coefficient
econ__pct_civilian_labor	-0.670417
demo__pct_non_hispanic_white	-0.499974
demo__pct_adults_bachelors_or_higher	-0.467134
demo__pct_adults_with_some_college	-0.363875
health__pct_excessive_drinking	-0.353254
demo__pct_asian	-0.163033
demo__pct_aged_65_years_and_older	-0.088123
demo__pct_female	-0.068065
demo__pct_below_18_years_of_age	0.039237
health__air_pollution_particulate_matter	0.058582
econ__pct_uninsured_children	0.098882
demo__pct_hispanic	0.105574
demo__birth_rate_per_1k	0.127506
health__pop_per_primary_care_physician	0.156942
demo__pct_adults_with_high_school_diploma	0.202928
demo__pct_american_indian_or_alaskan_native	0.236508
demo__death_rate_per_1k	0.244093
health__pop_per_dentist	0.268996
health__pct_adult_smoking	0.395457
health__motor_vehicle_crash_deaths_per_100k	0.420348
health__pct_physical_inacticity	0.437680
health__pct_adult_obesity	0.444293
demo__pct_non_hispanic_african_american	0.507048
health__pct_diabetes	0.537038
econ__pct_uninsured_adults	0.541712
health__pct_low_birthweight	0.565456
econ__pct_unemployment	0.592022
health__homicides_per_100k	0.621399
demo__pct_adults_less_than_a_high_school_diploma	0.680360

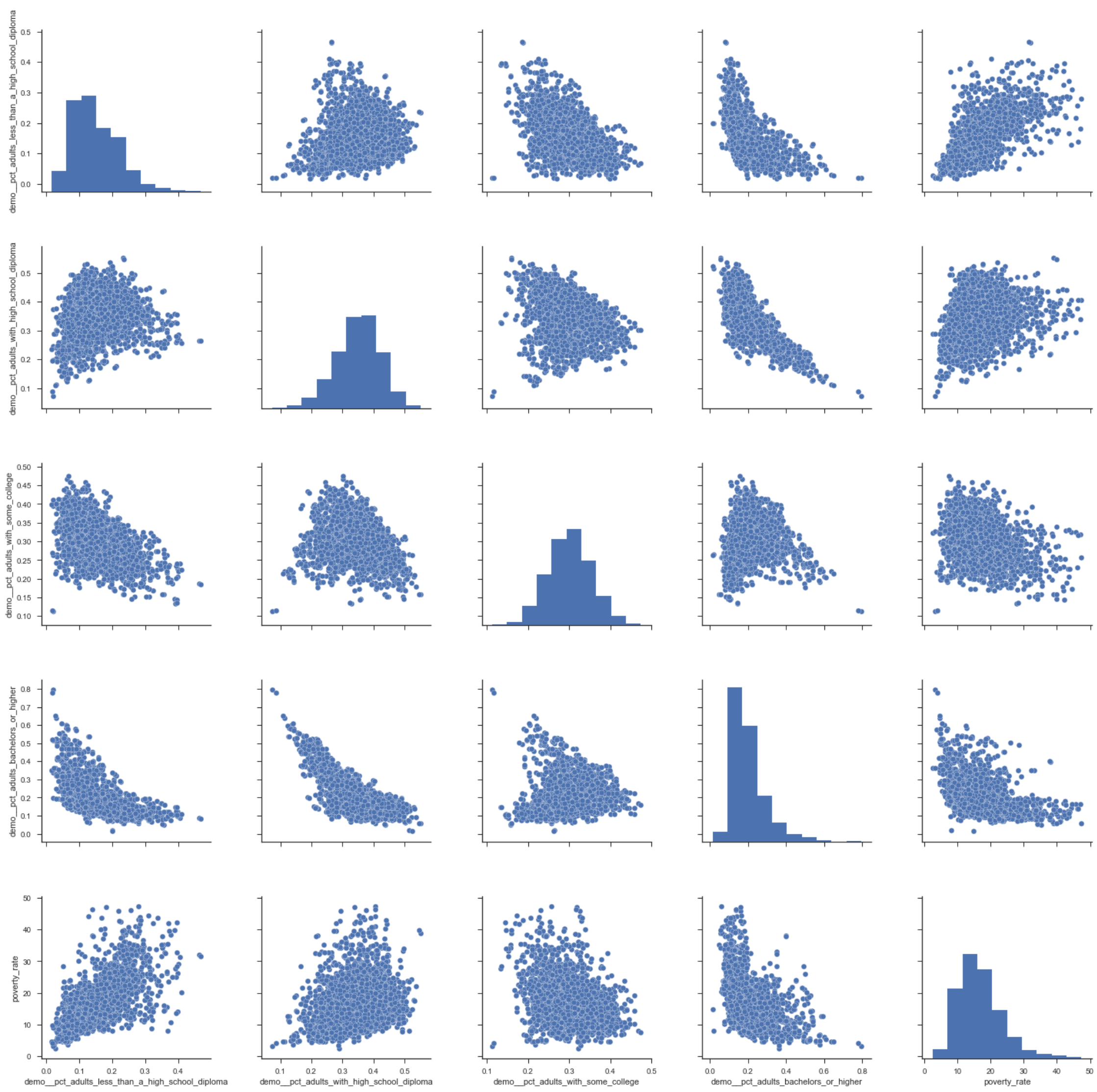
Scatter Plot Matrices After reading the 'Rural Poverty & Well-being' report it is clear that education, ethnicity and health related issues play an important role in predicting poverty. In this dataset are also added economic indicators of United States' counties. The scatter plot matrices of these four groups of socioeconomic indicators are shown here under. The scatter plot matrices visually confirms the finding of the correlation matrix.

NB: linear statistical transformations (sqrt, square, exponential, etc) were also applied to the target variable 'poverty_rate' but they did not improve substantially the correlation coefficients and the scatter plot matrices.

The correlation matrices and scatter plot matrices visually confirm that the variables correlate moderately strong with the target variable 'poverty_rate' seem to have a linear relationship.

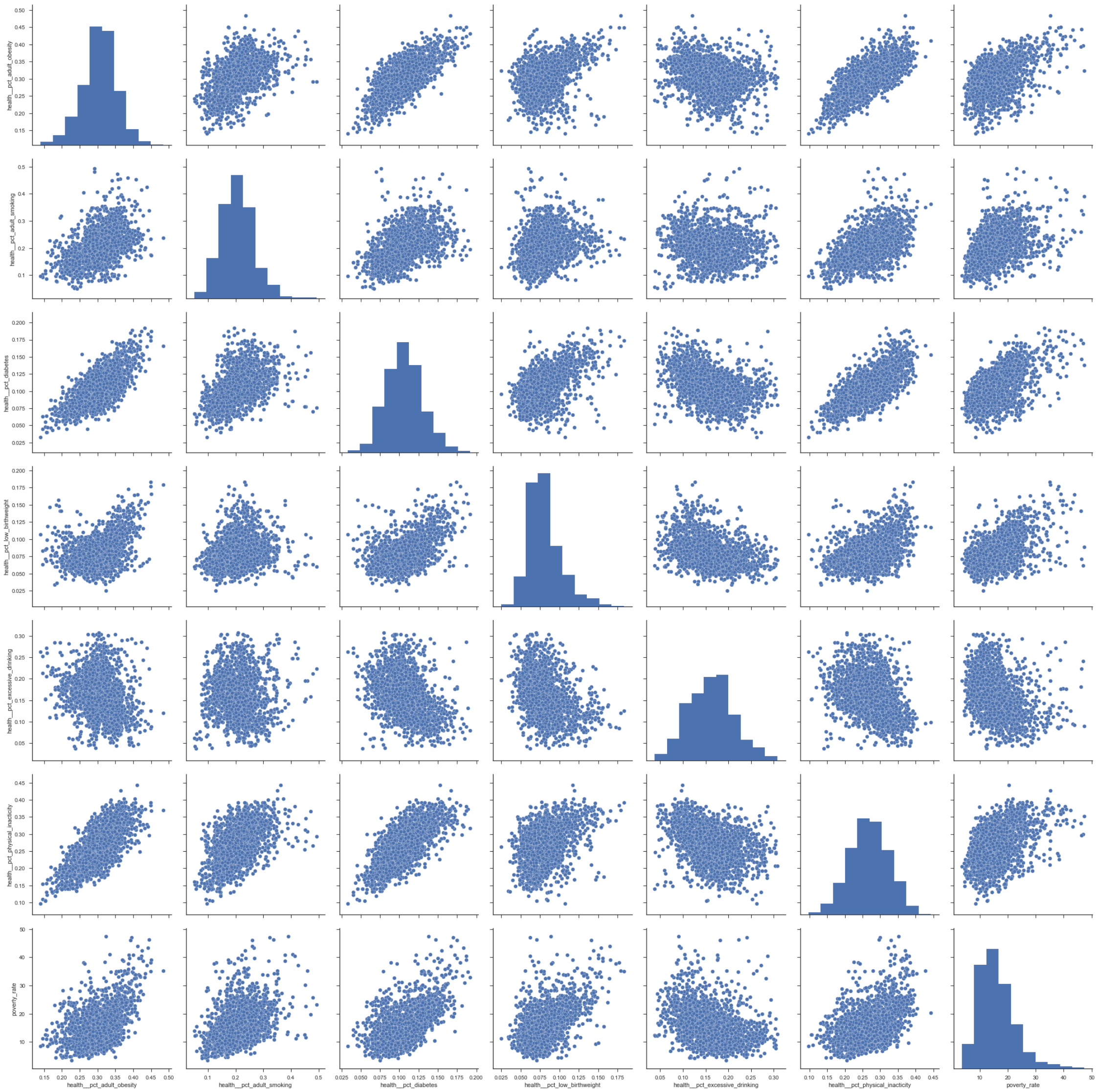
Educational Features Scatter Plot Matrices

```
In [213]: sns.set(style="ticks")
          scatter_educ = sns.pairplot(poverty.loc[:, ['demo__pct_adults_less_than_a_high_schoo
                                                        ,'demo__pct_adults_with_high_school_di
                                                        ,'demo__pct_adults_bachelors_or_higher
                                                        ,'poverty_rate']].dropna(), size=4)
```

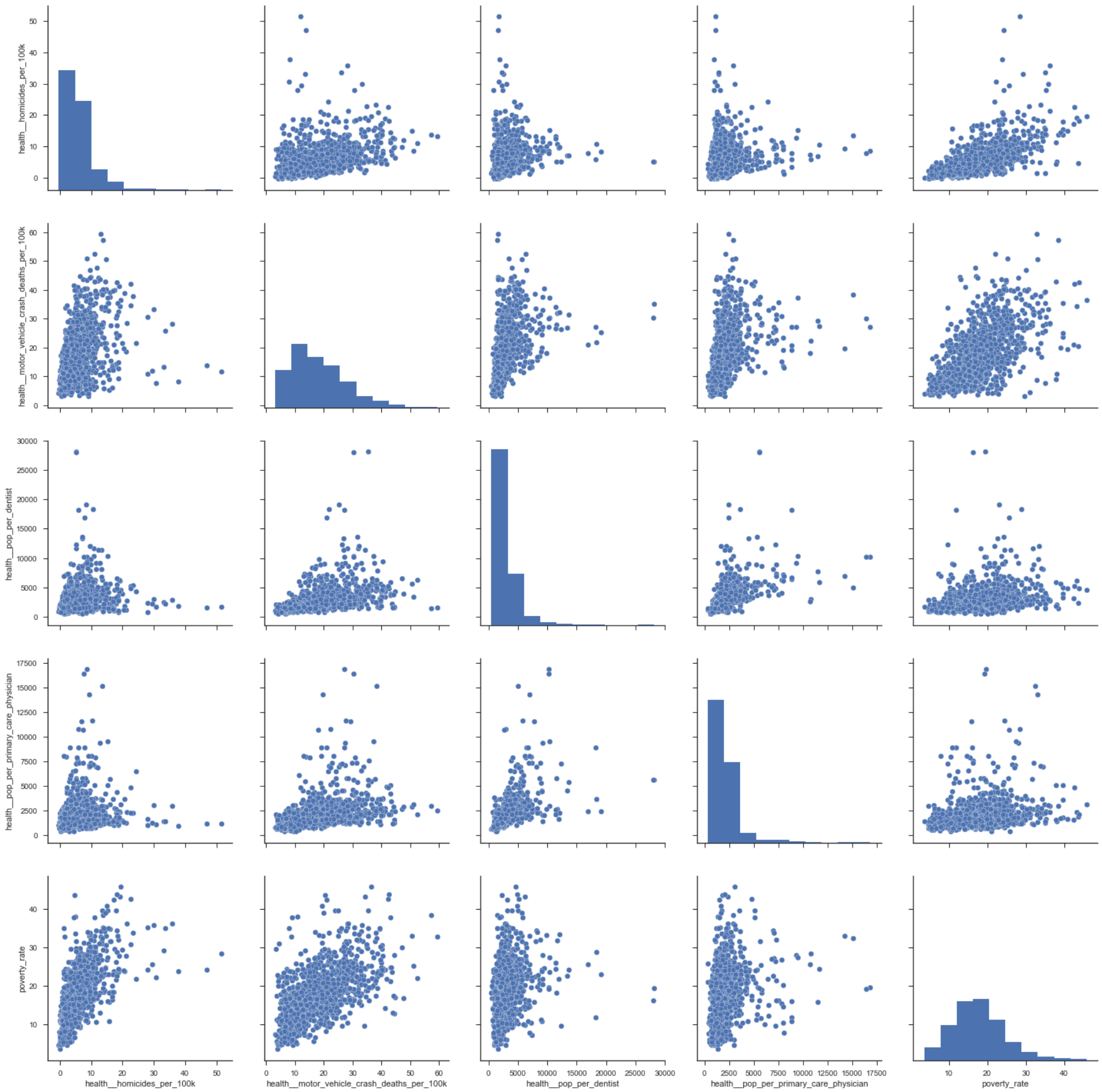


Health Features Scatter Plot Matrices

```
In [214]: scatter_health1 = sns.pairplot(poverty.loc[:, ['health__pct_adult_obesity','health__p
                                               ,'health__pct_diabetes','health__pct_lo
                                               ,'health__pct_excessive_drinking','heal
                                               ,'poverty_rate']].dropna(), size=4)
```

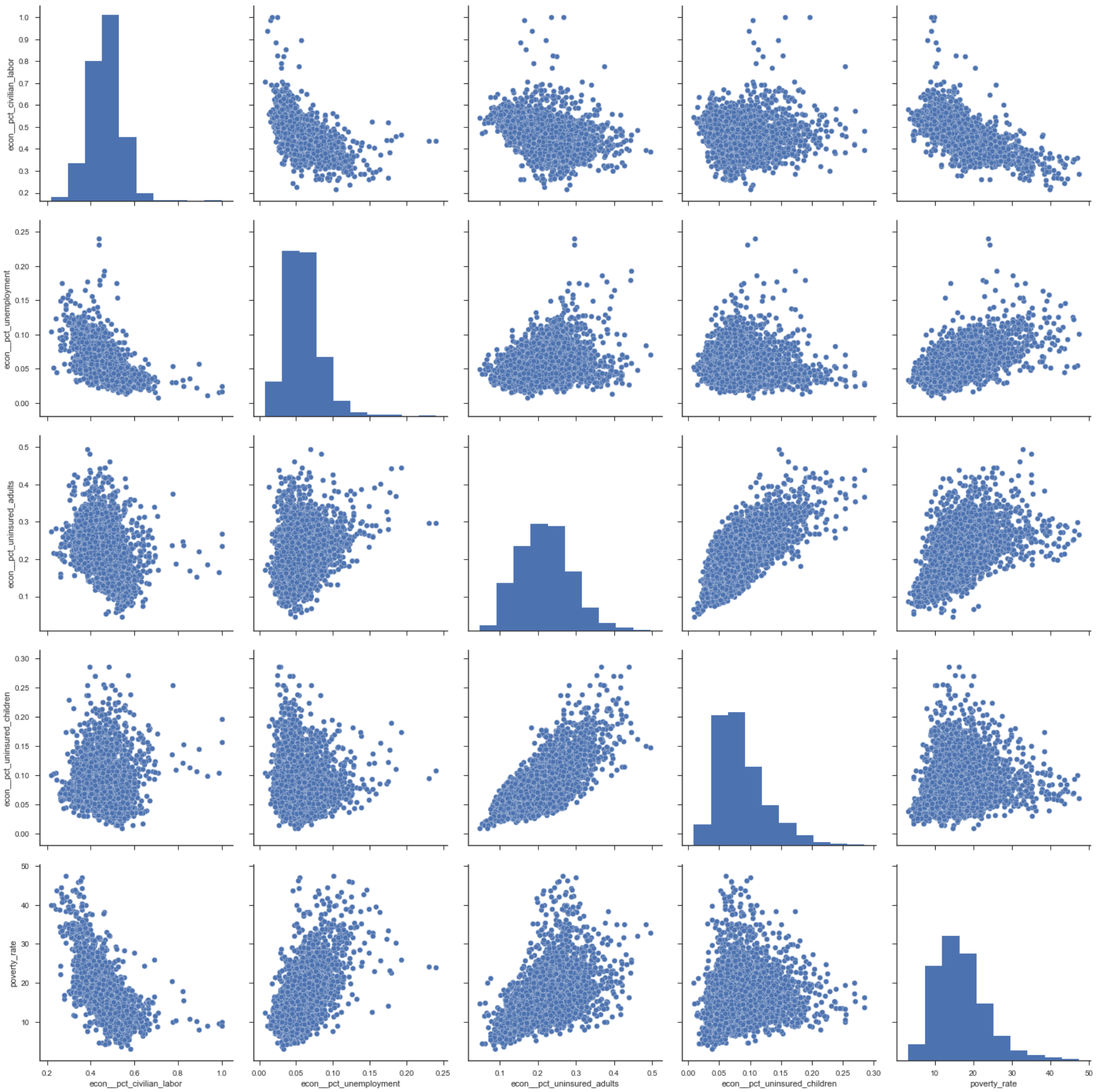


```
In [215]: scatter_health2 = sns.pairplot(poverty.loc[:, ['health__homicides_per_100k'
                                               ,'health__motor_vehicle_crash_deaths_pe
                                               ,'health__pop_per_dentist','health__pop
                                               ,'poverty_rate']].dropna(), size=4)
```



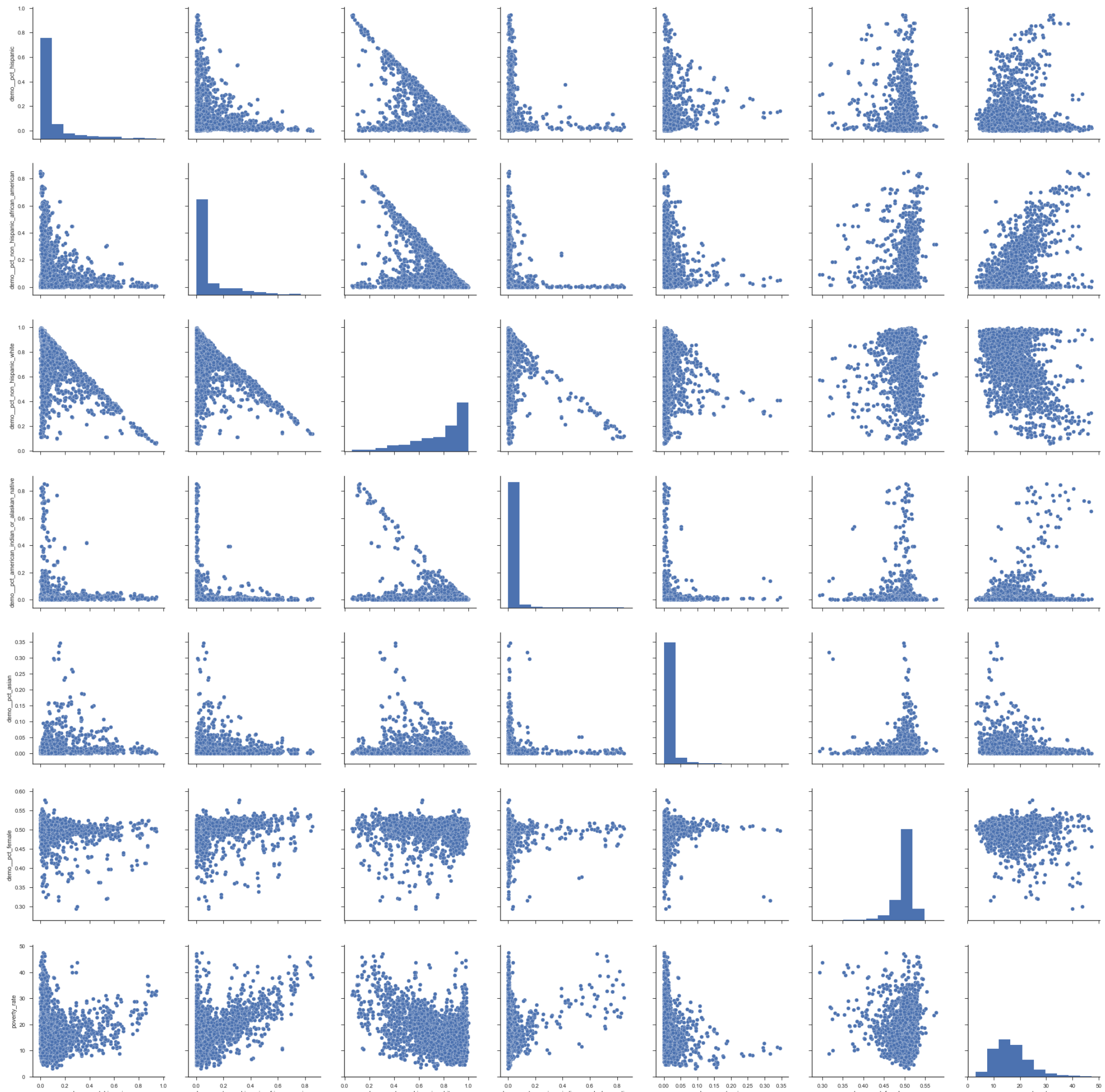
Economical Features Scatter Plot Matrices

```
In [216]: scatter_econ = sns.pairplot(poverty.loc[:, ['econ__pct_civilian_labor'
                                                      ,'econ__pct_unemployment'
                                                      ,'econ__pct_uninsured_adults','econ__p
                                                      ,'poverty_rate']].dropna(), size=4)
```



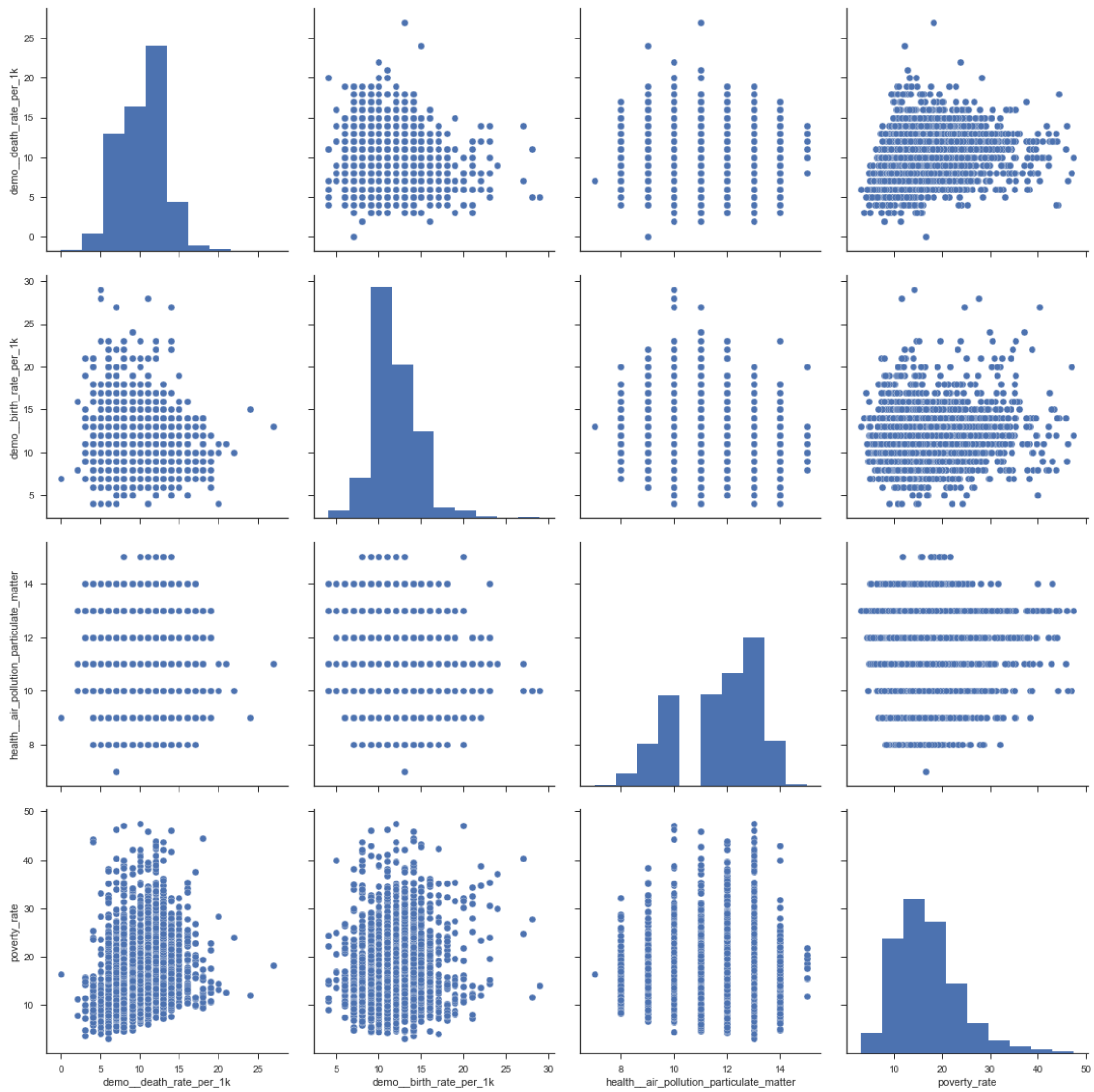
Demographic Features Scatter Plot Matrices

```
In [217]: scatter_ethnic = sns.pairplot(poverty.loc[:, ['demo__pct_hispanic'
                                                       ,'demo__pct_non_hispanic_african_americ
                                                       ,'demo__pct_non_hispanic_white','demo_
                                                       ,'demo__pct_asian', 'demo__pct_female'
                                                       ,'poverty_rate']].dropna(), size=4)
```



Categorical Features Scatter Plot Matrices These quantitative features behave like categorical features.

```
In [218]: scatter_non_ln = sns.pairplot(poverty.loc[:, ['demo__death_rate_per_1k'
                                                      ,'demo__birth_rate_per_1k'
                                                      ,'health__air_pollution_particulate_ma
                                                      ,'poverty_rate']].dropna(), size=4)
```



Creation and Visualization of New Categorical Variables From observing the scatter plot matrices of the features 'demo__death_rate_per_1k', 'demo__birth_rate_per_1k' and 'health__air_pollution_particulate_matter' is clear that these quantitative variables behave like categorical variables. They will be transformed into categorical features by binning them.

```
In [219]: def create_birthrate_cat(input_df):
              cats = [ "birthrate {0} - {1}".format(i, i + 5) for i in range(0, 40, 5) ]
              input_df.loc[:,'birth_rate_cat'] = pd.cut(input_df.demo__birth_rate_per_1k, range
              input_df.loc[:,'birth_rate_cat'] = input_df.birth_rate_cat.astype('category')
              input_df.loc[:,'birth_rate_cat'] = input_df.birth_rate_cat.cat.set_categories(ca
              return input_df
```

```
In [220]: def create_deathrate_cat(input_df):
              cats = [ "deathrate {0} - {1}".format(i, i + 5) for i in range(0, 40, 5) ]
```

```
        input_df.loc[:,'death_rate_cat'] = pd.cut(input_df.demo__death_rate_per_1k, range
        input_df.loc[:,'death_rate_cat'] = input_df.death_rate_cat.astype('category')
        input_df.loc[:,'death_rate_cat'] = input_df.death_rate_cat.cat.set_categories(ca
        return input_df
```

```
In [221]: def create_air_poll_cat(input_df):
              cats = [ "airpoll {0} - {1}".format(i, i + 5) for i in range(0, 35, 5) ]
              input_df.loc[:,'air_poll_cat'] = pd.cut(input_df.health__air_pollution_particula
              input_df.loc[:,'air_poll_cat'] = input_df.air_poll_cat.astype('category')
              input_df.loc[:,'air_poll_cat'] = input_df.air_poll_cat.cat.set_categories(cats,
              return input_df
```

```
In [222]: def create_features(input_df):
              input_df = create_birthrate_cat(input_df)
              input_df = create_deathrate_cat(input_df)
              input_df = create_air_poll_cat(input_df)
              return input_df
```

```
In [223]: poverty = create_features(poverty)
```

1.4 Data Preparation

This phase involves mostly the cleaning, scaling and one hot encoding of features: * dropping redundant features * converting features to the right type * missing values are replaced by the respective median value of the feature. The median is preferred over the mean because it is less sensible to skewed data and gives a better measure of centrality. * features are scaled to have the same scale. The MinMaxScaler is applied to the features "health__homicides_per_100k' and 'health__motor_vehicle_crash_deaths_per_100k' to scale them the same way as other quantitative variables that are in percentages between 0 and 1. * One hot encoding of the categorical variables is performed

```
In [224]: def drop_features(input_df):
              result_df = input_df.drop(columns=['health__air_pollution_particulate_matter'
                                              ,'demo__death_rate_per_1k', 'demo__birth_rate_
                                              ,'pct_65years_cat','area__urban_influence','yr
              return result_df
```

```
In [225]: poverty_clean = drop_features(poverty)
```

```
In [226]: def convert_to_cat(input_df):
              input_df.loc[:,'area__rucc'] = input_df.area__rucc.astype("category")
              input_df.loc[:,'econ__economic_typology'] = input_df.econ__economic_typology.ast
              return input_df
```

```
In [227]: poverty_clean = convert_to_cat(poverty_clean)
```

```
In [228]: dtypes_tmp = poverty_clean.dtypes
```

```
In [229]: def clean_nans(input_df):
              result_df = input_df.fillna(poverty_clean.median())
              return result_df
```

In [230]:
```
poverty_clean = clean_nans(poverty_clean)
```

In [231]:
```
clean_tmp = poverty_clean.isnull().sum()
```

In [232]:
```
def scale_features(input_df):
    input_scale = input_df.loc[:,['health__homicides_per_100k'
                                   ,'health__motor_vehicle_crash_deaths_per_100k'
                                  ,'health__pop_per_dentist'
                                  ,'health__pop_per_primary_care_physician']]

    input_scaled = pd.DataFrame(MinMaxScaler().fit_transform(input_scale), columns=in

    input_df.loc[:,'health__homicides_per_100k'] = input_scaled.loc[:,'health__homic
    input_df.loc[:,'health__motor_vehicle_crash_deaths_per_100k'] = input_scaled.loc
    input_df.loc[:,'health__pop_per_dentist'] = input_scaled.loc[:,'health__pop_per_
    input_df.loc[:,'health__pop_per_primary_care_physician'] = input_scaled.loc[:,'he
    return input_df
```

In [233]:
```
poverty_clean = scale_features(poverty_clean)
```

In [234]:
```
def cat_to_dummies(input_df):
    result_df = pd.get_dummies(input_df, dummy_na=True, columns=['area__rucc','econ_
                                                               ,'birth_rate_cat','de
                                                               ,'aui_pct65y_cat'])
    return result_df
```

In [235]:
```
poverty_clean = cat_to_dummies(poverty_clean)
```

In [236]:
```
shape_tmp = poverty_clean.shape
```

1.5 Modeling and Evaluation

In this phase two models are compared with each other using the RMSE evaluation metric: * Least Square Linear Model after applying recursive feature selection to create a linear model with the most important features * An AdaBoostRegressor which is an ensemble learning model of decision trees.

The best RMSE scores obtained by these two models are:

Model	RMSE
AdaBoostRegressor	2.7853
Linear Regression	2.9297

The AdaBoostRegressor happens to be more precise than the Least Squares Linear Model because it can handle non linear relationships. The AdaBoostRegressor is chosen as the regression model to predict poverty rates for United States Counties.

In [237]:
```
rng = np.random.RandomState(0)
```

```
In [238]: poverty_X = poverty_clean.drop(columns=['row_id','poverty_rate'], axis=1)
          poverty_y = poverty_clean.poverty_rate
```

```
In [239]: # use r2 adjusted in the future
          scoring = {'r2':'r2','mse': make_scorer(mean_squared_error, greater_is_better=False)]
```

```
In [240]: inner_cv = ShuffleSplit(n_splits=5, test_size=0.3, random_state=rng)
          outer_cv = ShuffleSplit(n_splits=5, test_size=0.3, random_state=rng)
```

1.5.1 Recursive Feature Selection Linear Regression

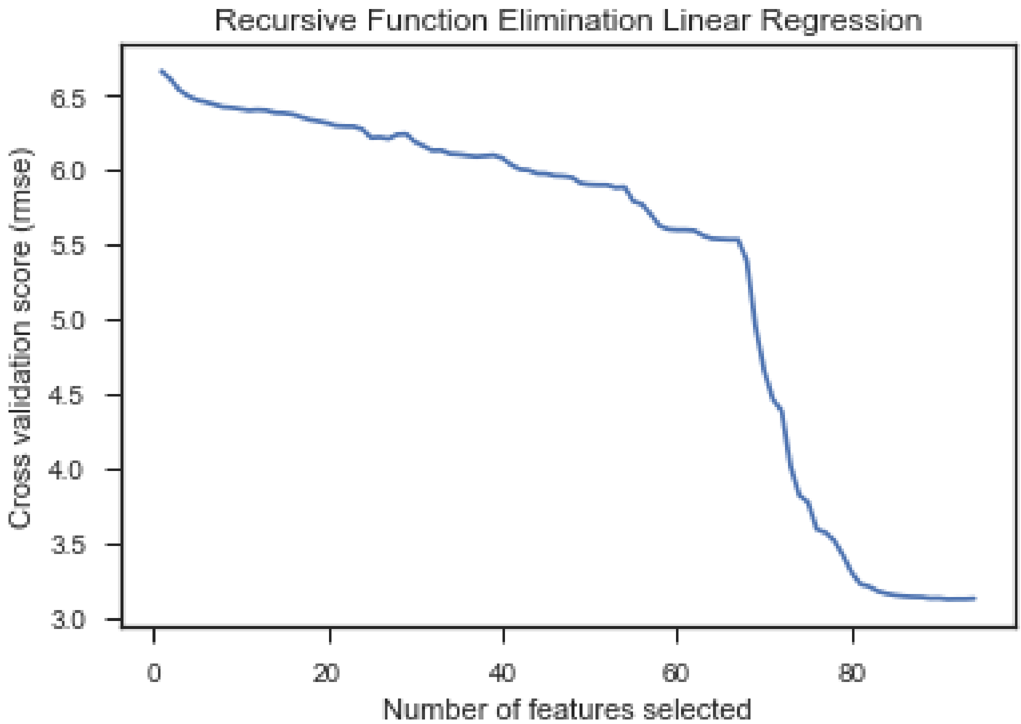
```
In [241]: caching = mkdtemp()

          mse = make_scorer(mean_squared_error, greater_is_better=False)

          rfecv = RFECV(estimator=LinearRegression(), step=1, cv=inner_cv, scoring=mse)

          rfecv.fit(poverty_X, poverty_y)

          print("Optimal number of features : %d" % rfecv.n_features_)
```

```
Optimal number of features : 91
```

```
In [242]: pprint('RMSE score: %f' % np.sqrt(np.abs(rfecv.grid_scores_[rfecv.n_features_])))
```

```
'RMSE score: 3.120846'
```

```
In [243]: plt.figure()
          plt.title('Recursive Function Elimination Linear Regression')
          plt.xlabel("Number of features selected")
          plt.ylabel("Cross validation score (rmse)")
          plt.plot(range(1, len(rfecv.grid_scores_) + 1), np.sqrt(np.abs(rfecv.grid_scores_)))
          plt.show()
```



1.5.2 Nested Cross Validation AdaBoostRegressor Vs Linear Regression

Using nested cross validation the AdaBoostRegressor is compared with the linear regression model. The AdaBoostRegressor wins the lowest RMSE score.

In [179]:
```
cachedir = mkdtemp()
estimators = [('reg_model', LinearRegression())]
regr_pipe = Pipeline(estimators, memory=cachedir)
```

In [180]:
```
adaReg = AdaBoostRegressor(base_estimator=DecisionTreeRegressor(max_depth=13, splitte
                                                               , random_state=rng)
                                     , n_estimators=600, loss='linear', learning_rate=1, randon
```

In [181]:
```
param_grid = dict(reg_model=[rfecv, adaReg])
```

In [182]:
```
reg_grid = GridSearchCV(estimator=regr_pipe, param_grid=param_grid, scoring=scoring,
                              , error_score=0, refit='mse')
reg_pred = reg_grid.fit(poverty_X, poverty_y)
```

Out[182]:
```
Pipeline(memory='/var/folders/_j/vyb4dyfx2wq850vj9vh25wy40000gn/T/tmpjobrnls4',
     steps=[('reg_model', AdaBoostRegressor(base_estimator=DecisionTreeRegressor(cri
           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...oss='linear', n_estimato
         random_state=<mtrand.RandomState object at 0x1a23e10dc8>))])
```

```
In [183]: train_scores = cross_validate(reg_grid, poverty_X, poverty_y, cv=outer_cv, scoring=sc
          pprint('RMSE score: %f' % np.average(np.sqrt(np.abs(train_scores['test_mse']))))
```

```
0.87776577189611893
2.3620582669780799
```

1.5.3 Recursive Feature Selection AdaBoostRegressor

To improve the AdaBoostRegressor even more, the best features are selected using recursive feature elimination or backwards elimination.

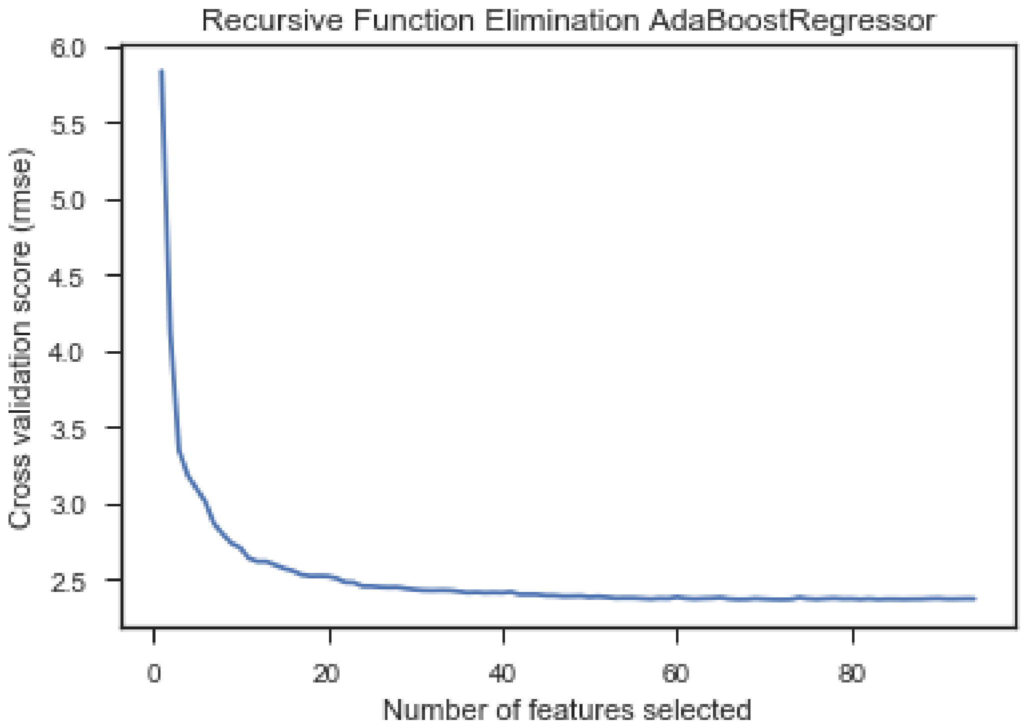
```
In [245]: mse = make_scorer(mean_squared_error, greater_is_better=False)

          rfecv = RFECV(estimator=adaReg, step=1, cv=inner_cv, scoring=mse)

          rfecv.fit(poverty_X, poverty_y)

          print("Optimal number of features : %d" % rfecv.n_features_)
```

```
In [ ]: pprint('RMSE score: %f' % np.sqrt(np.abs(rfecv.grid_scores_[rfecv.n_features_])))
```

```
In [184]: train_scores = cross_validate(rfecv, poverty_X, poverty_y, cv=outer_cv, scoring=scori
          pprint('RMSE score: %f' % np.average(np.sqrt(np.abs(train_scores['test_mse']))))
```

```
0.87450742944546123
2.3514823434788399
```

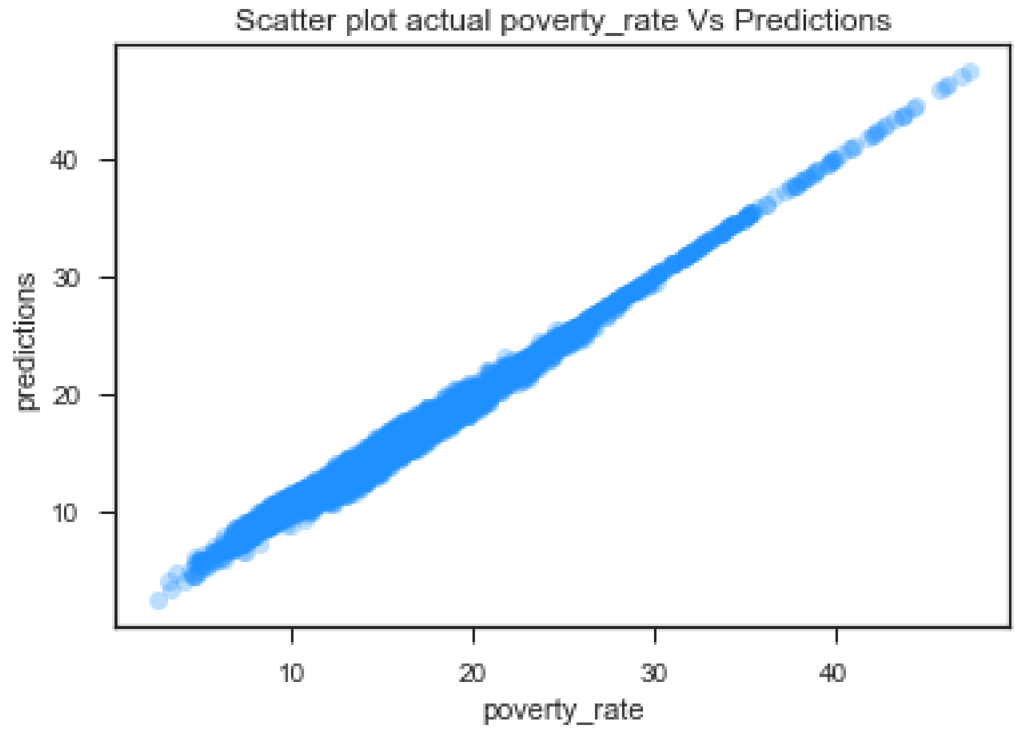
```
In [185]: plt.figure()
          plt.title('Recursive Function Elimination AdaBoostRegressor')
          plt.xlabel("Number of features selected")
          plt.ylabel("Cross validation score (rmse)")
          plt.plot(range(1, len(rfecv.grid_scores_) + 1), np.sqrt(np.abs(rfecv.grid_scores_)))
          plt.show()
```



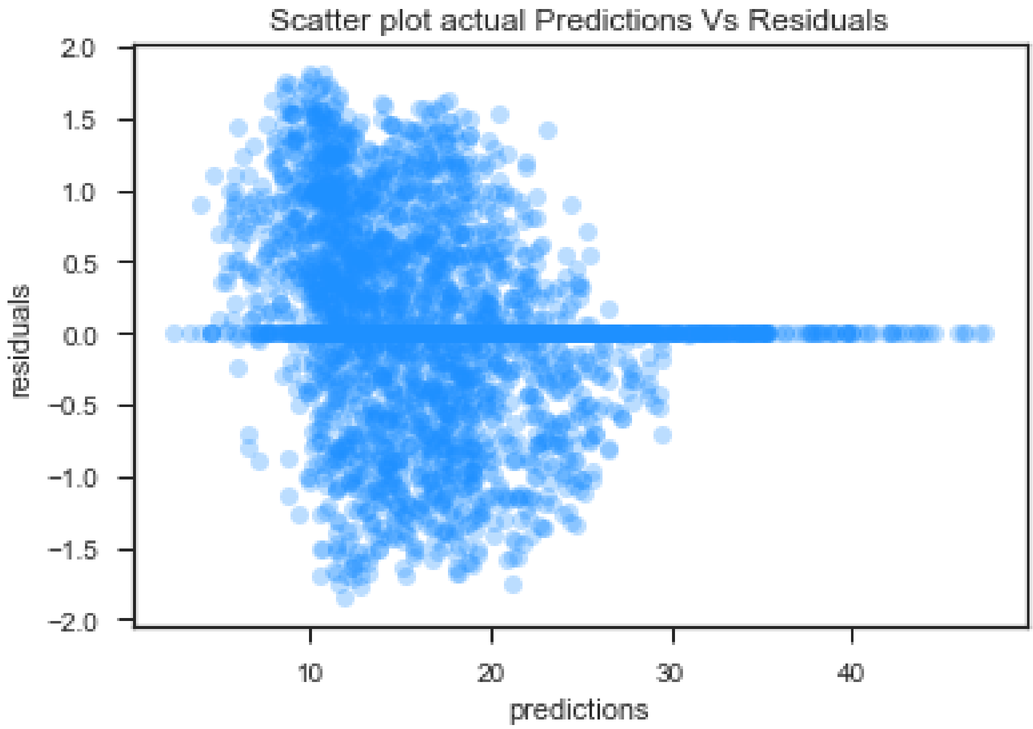
1.5.4 Analysis of Predictions and Residuals

The Analysis of the quality of the predictions and residuals shows that the accuracy of the AdaBoostRegressor is high. However the AdaBoostRegressor probably slightly overfits the data.

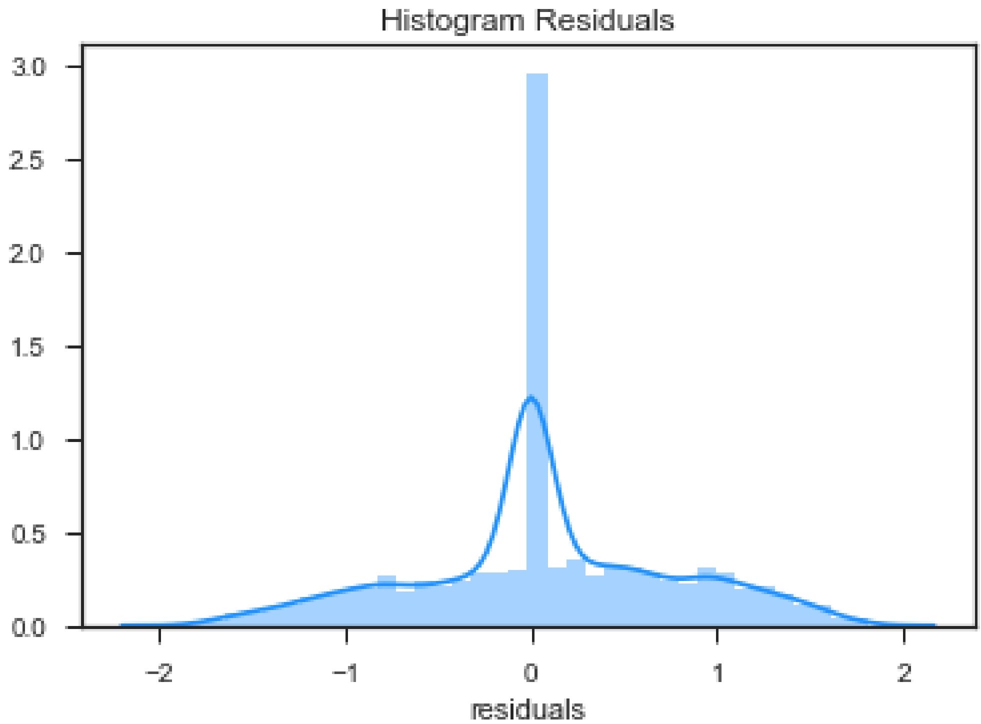
```
In [184]: sc1_tmp = sns.regplot(x=poverty_y, y=reg_grid.predict(poverty_X), fit_reg=False, colo
          tmp = sc1_tmp.set_ylabel('predictions')
          tmp = sc1_tmp.set_title('Scatter plot actual poverty_rate Vs Predictions')
```




```
In [185]: sc2_tmp = sns.regplot(x=reg_grid.predict(poverty_X), y=reg_grid.predict(poverty_X) -
                                , fit_reg=False, color='dodgerblue', scatter_kws={'alpha':0.3}
          tmp = sc2_tmp.set_xlabel('predictions')
          tmp = sc2_tmp.set_ylabel('residuals')
          tmp = sc2_tmp.set_title('Scatter plot actual Predictions Vs Residuals')
```



In [186]:
```
residuals = reg_grid.predict(poverty_X) - poverty_y
residuals = residuals.rename('residuals')
ht_pov = sns.distplot(residuals, color='dodgerblue').set_title('Histogram Residuals')
```




```
In [246]: poverty_test = pd.read_csv('./Microsoft_-_DAT102x_Predicting_Poverty_in_the_United_St

In [247]: #Create Features
          poverty_test = create_old_age_cat(poverty_test)
          poverty_test = create_aui_pct65y_cat(poverty_test)
          poverty_test = create_features(poverty_test)

          #Convert to correct type
          poverty_test = convert_to_cat(poverty_test)

          #Drop Features
          poverty_row_id = poverty_test.row_id
          poverty_test = drop_features(poverty_test)
          poverty_test = poverty_test.drop(columns=['row_id'], axis=1)

          #Replace NANs
          poverty_test_clean = poverty_test.fillna(poverty_test.median())
          poverty_test_clean = cat_to_dummies(poverty_test_clean)

          #Scale Features
          poverty_test_clean = scale_features(poverty_test_clean)

In [248]: #Create Prediction
          submission = pd.DataFrame(reg_grid.predict(poverty_test_clean))
          submission = np.clip(submission,0.00, 100.00)
```

```
In [249]: poverty_submission = pd.concat([poverty_row_id, submission], axis=1)
          poverty_submission = poverty_submission.rename(index=str, columns={0: 'poverty_rate'
          poverty_submission = poverty_submission.round({'poverty_rate':2})

In [250]: poverty_submission.to_csv(path_or_buf='./MV_Poverty_Submission_AdaReg.csv', index=Fa
```

1.6 Conclusion

The Regression analysis shows that is possible to build an accurate regression model to predict poverty rates of United States' counties using an AdaBoostRegressor. From the data exploration phase it is clear that economical, educational, ethnical and health related factors play an important role in predicting poverty. However is recursive function elemination is used to determine the optimal number of features that leads to the best prediction.