Prediction of United States' Counties Poverty Rates[¶](#Prediction-of-United-States'-Counties-Poverty-Rates)

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# Executive Summary[¶](#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 a regression model. The regression model created is able to predict United States' counties poverty rates with an RMSE of 2.7847.

In the data understanding phase was discovered that the features in the table here under 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. More importantly recursive function elimination or backwards selection 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 |
| area\_\_urban\_influence | Urban influence codes |
| 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](https://www.ers.usda.gov/topics/rural-economy-population/rural-poverty-well-being/poverty-overview.aspx)' 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.

## Business Understanding[¶](#Business-Understanding)

As described in the online report the '[Rural Poverty & Well-being](https://www.ers.usda.gov/topics/rural-economy-population/rural-poverty-well-being/poverty-overview.aspx)': "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.

## Data Understanding[¶](#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[¶](#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.

#### Individual Feature Statistics[¶](#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).

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | count | unique | top | freq | mean | std | min | 25% | 50% | 75% | max |
| area\_\_rucc | 3198 | 9 | Nonmetro - Urban population of 2,500 to 19,999... | 608 | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| area\_\_urban\_influence | 3198 | 12 | Small-in a metro area with fewer than 1 millio... | 692 | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| econ\_\_economic\_typology | 3198 | 6 | Nonspecialized | 1266 | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| econ\_\_pct\_civilian\_labor | 3198 | NaN | NaN | NaN | 0.467071 | 0.074541 | 0.217 | 0.42 | 0.467 | 0.514 | 1 |
| econ\_\_pct\_unemployment | 3198 | NaN | NaN | NaN | 0.0596104 | 0.0228497 | 0.008 | 0.044 | 0.057 | 0.071 | 0.24 |
| econ\_\_pct\_uninsured\_adults | 3196 | NaN | NaN | NaN | 0.217534 | 0.0673718 | 0.046 | 0.166 | 0.216 | 0.262 | 0.495 |
| econ\_\_pct\_uninsured\_children | 3196 | NaN | NaN | NaN | 0.0859202 | 0.0400046 | 0.009 | 0.057 | 0.077 | 0.105 | 0.285 |
| demo\_\_pct\_female | 3196 | NaN | NaN | NaN | 0.498781 | 0.0242508 | 0.294 | 0.493 | 0.503 | 0.512 | 0.576 |
| demo\_\_pct\_below\_18\_years\_of\_age | 3196 | NaN | NaN | NaN | 0.227763 | 0.0342909 | 0.098 | 0.207 | 0.226 | 0.24525 | 0.417 |
| demo\_\_pct\_aged\_65\_years\_and\_older | 3196 | NaN | NaN | NaN | 0.170137 | 0.0435937 | 0.043 | 0.142 | 0.167 | 0.194 | 0.355 |
| demo\_\_pct\_hispanic | 3196 | NaN | NaN | NaN | 0.0902334 | 0.142707 | 0 | 0.019 | 0.035 | 0.088 | 0.945 |
| demo\_\_pct\_non\_hispanic\_african\_american | 3196 | NaN | NaN | NaN | 0.0911167 | 0.147104 | 0 | 0.006 | 0.022 | 0.09625 | 0.855 |
| demo\_\_pct\_non\_hispanic\_white | 3196 | NaN | NaN | NaN | 0.770207 | 0.207903 | 0.06 | 0.648 | 0.854 | 0.936 | 0.998 |
| demo\_\_pct\_american\_indian\_or\_alaskan\_native | 3196 | NaN | NaN | NaN | 0.0246586 | 0.0846341 | 0 | 0.002 | 0.007 | 0.014 | 0.852 |
| demo\_\_pct\_asian | 3196 | NaN | NaN | NaN | 0.0133035 | 0.0253656 | 0 | 0.003 | 0.007 | 0.013 | 0.346 |
| demo\_\_pct\_adults\_less\_than\_a\_high\_school\_diploma | 3198 | NaN | NaN | NaN | 0.148794 | 0.0682547 | 0.016129 | 0.0974683 | 0.133501 | 0.195171 | 0.466867 |
| demo\_\_pct\_adults\_with\_high\_school\_diploma | 3198 | NaN | NaN | NaN | 0.3503 | 0.0705342 | 0.0728205 | 0.305915 | 0.355701 | 0.399197 | 0.551689 |
| demo\_\_pct\_adults\_with\_some\_college | 3198 | NaN | NaN | NaN | 0.301366 | 0.0524976 | 0.112821 | 0.265362 | 0.301595 | 0.335972 | 0.474216 |
| demo\_\_pct\_adults\_bachelors\_or\_higher | 3198 | NaN | NaN | NaN | 0.19954 | 0.0891577 | 0.013986 | 0.13884 | 0.177247 | 0.233258 | 0.794872 |
| demo\_\_birth\_rate\_per\_1k | 3198 | NaN | NaN | NaN | 11.677 | 2.73952 | 4 | 10 | 11 | 13 | 29 |
| demo\_\_death\_rate\_per\_1k | 3198 | NaN | NaN | NaN | 10.3011 | 2.78614 | 0 | 8 | 10 | 12 | 27 |
| health\_\_pct\_adult\_obesity | 3196 | NaN | NaN | NaN | 0.307599 | 0.043404 | 0.14 | 0.284 | 0.309 | 0.334 | 0.484 |
| health\_\_pct\_adult\_smoking | 2734 | NaN | NaN | NaN | 0.213519 | 0.0630903 | 0.05 | 0.171 | 0.211 | 0.24975 | 0.526 |
| health\_\_pct\_diabetes | 3196 | NaN | NaN | NaN | 0.109287 | 0.0231967 | 0.033 | 0.094 | 0.109 | 0.124 | 0.197 |
| health\_\_pct\_low\_birthweight | 3016 | NaN | NaN | NaN | 0.0835345 | 0.0223822 | 0.025 | 0.068 | 0.08 | 0.095 | 0.232 |
| health\_\_pct\_excessive\_drinking | 2220 | NaN | NaN | NaN | 0.164832 | 0.0502321 | 0.038 | 0.129 | 0.164 | 0.196 | 0.358 |
| health\_\_pct\_physical\_inacticity | 3196 | NaN | NaN | NaN | 0.277309 | 0.0529475 | 0.097 | 0.243 | 0.28 | 0.313 | 0.443 |
| health\_\_air\_pollution\_particulate\_matter | 3170 | NaN | NaN | NaN | 11.6265 | 1.54493 | 7 | 10 | 12 | 13 | 15 |
| health\_\_homicides\_per\_100k | 1231 | NaN | NaN | NaN | 5.95075 | 5.06337 | -0.39 | 2.66 | 4.84 | 7.825 | 51.49 |
| health\_\_motor\_vehicle\_crash\_deaths\_per\_100k | 2781 | NaN | NaN | NaN | 21.1161 | 10.517 | 3.09 | 13.46 | 19.63 | 26.47 | 110.45 |
| health\_\_pop\_per\_dentist | 2954 | NaN | NaN | NaN | 3431.44 | 2569.44 | 339 | 1812.25 | 2690 | 4089.75 | 28129 |
| health\_\_pop\_per\_primary\_care\_physician | 2968 | NaN | NaN | NaN | 2551.35 | 2100.48 | 189 | 1419 | 1999 | 2859 | 23400 |
| yr | 3198 | 2 | b | 1599 | NaN | NaN | NaN | NaN | NaN | NaN | NaN |

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

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | count | mean | std | min | 25% | 50% | 75% | max |
| poverty\_rate | 3198.0 | 16.817136 | 6.697969 | 2.5 | 12.0 | 15.8 | 20.3 | 47.4 |

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.

![](data:image/png;base64;base64,)

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.

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### Data Exploration and Visualization of Categorical Variables[¶](#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.

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### Data Exploration and Visualization of Quantitative Variables[¶](#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[¶](#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[¶](#Scatter-Plot-Matrices)

After reading the '[Rural Poverty & Well-being](https://www.ers.usda.gov/topics/rural-economy-population/rural-poverty-well-being/poverty-overview.aspx)' 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[¶](#Educational-Features-Scatter-Plot-Matrices)

![](data:image/png;base64;base64,)

##### Health Features Scatter Plot Matrices[¶](#Health-Features-Scatter-Plot-Matrices)

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##### Economical Features Scatter Plot Matrices[¶](#Economical-Features-Scatter-Plot-Matrices)

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##### Demographic Features Scatter Plot Matrices[¶](#Demographic-Features-Scatter-Plot-Matrices)

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##### Categorical Features Scatter Plot Matrices[¶](#Categorical-Features-Scatter-Plot-Matrices)

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#### Creation and Visualization of New Categorical Variables[¶](#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.

## Data Preparation[¶](#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

## Modeling and Evaluation[¶](#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 | 2.7847 |
| 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.

### Recursive Feature Selection Linear Regression[¶](#Recursive-Feature-Selection-Linear-Regression)

Optimal number of features : 73

'RMSE score: 3.121806'

![](data:image/png;base64;base64,)

### Nested Cross Validation AdaBoostRegressor Vs Linear Regression[¶](#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.

'RMSE score: 2.428183'

### Recursive Feature Selection AdaBoostRegressor[¶](#Recursive-Feature-Selection-AdaBoostRegressor)

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

Optimal number of features : 62

'RMSE score: 2.406639'

'RMSE score: 2.366428'

![](data:image/png;base64;base64,)

### Analysis of Predictions and Residuals[¶](#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.

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## Conclusion[¶](#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.