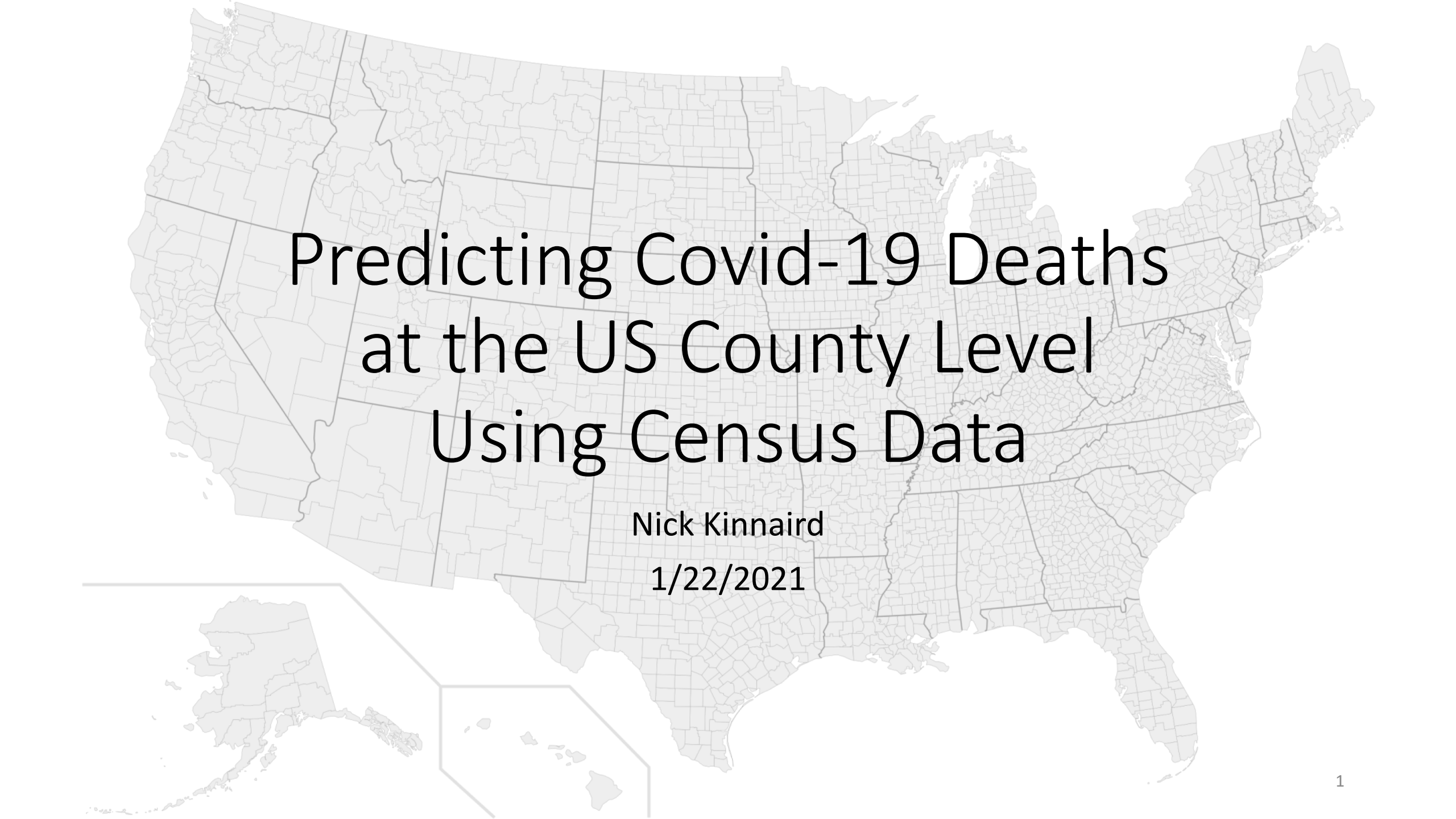


Predicting Covid-19 Deaths at the US County Level Using Census Data

Nick Kinnaird

1/22/2021

Idea: Knowing which counties are more at risk means resources can be deployed more efficiently.

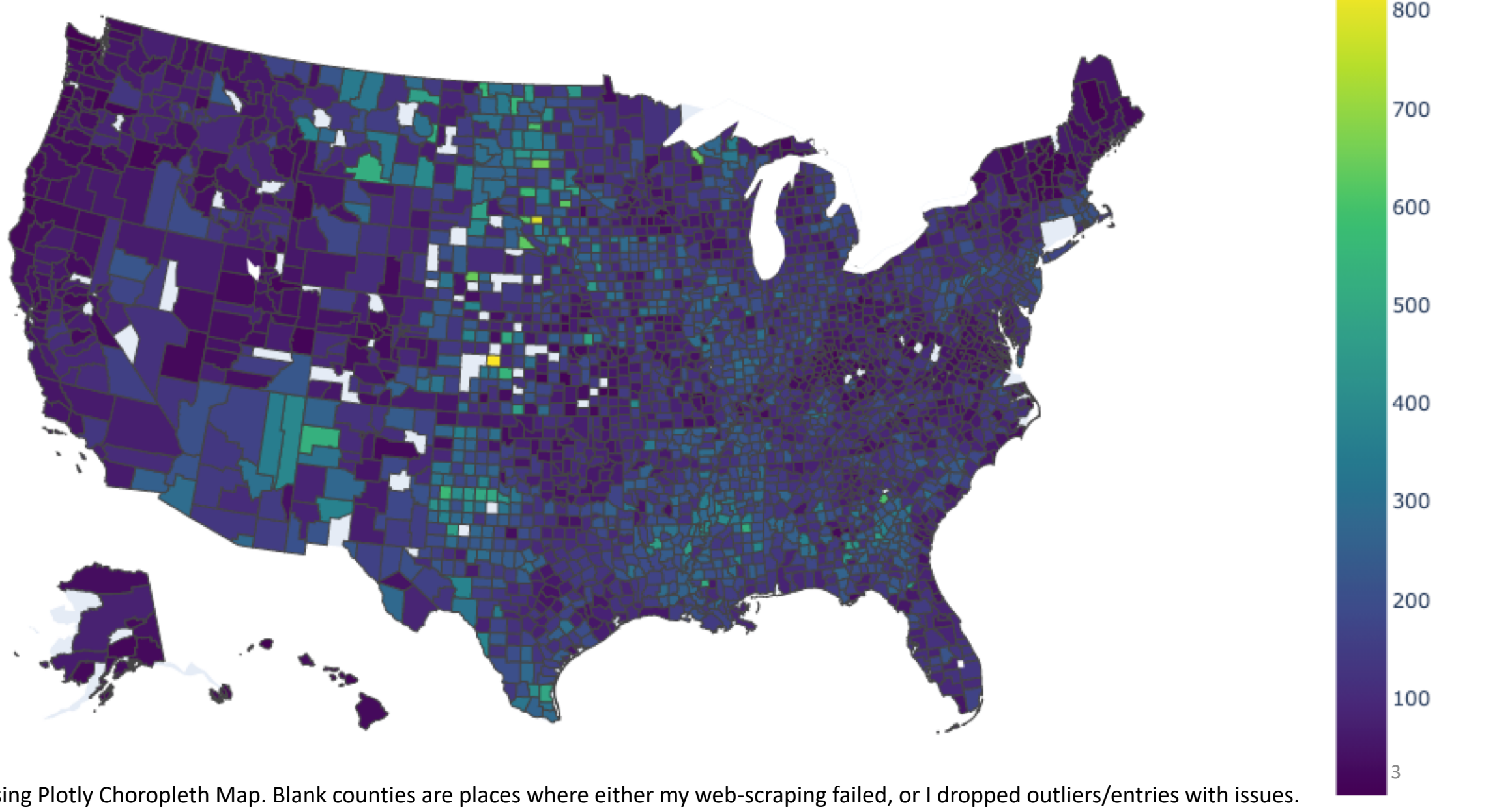
Target variable: Cumulative Covid-19 deaths per county scaled by population

- Data acquired from the NYT Covid-19 Github repository
- Dated 1/18/2021
- ~3000 counties

Features: US Census data scraped from the Census Bureau

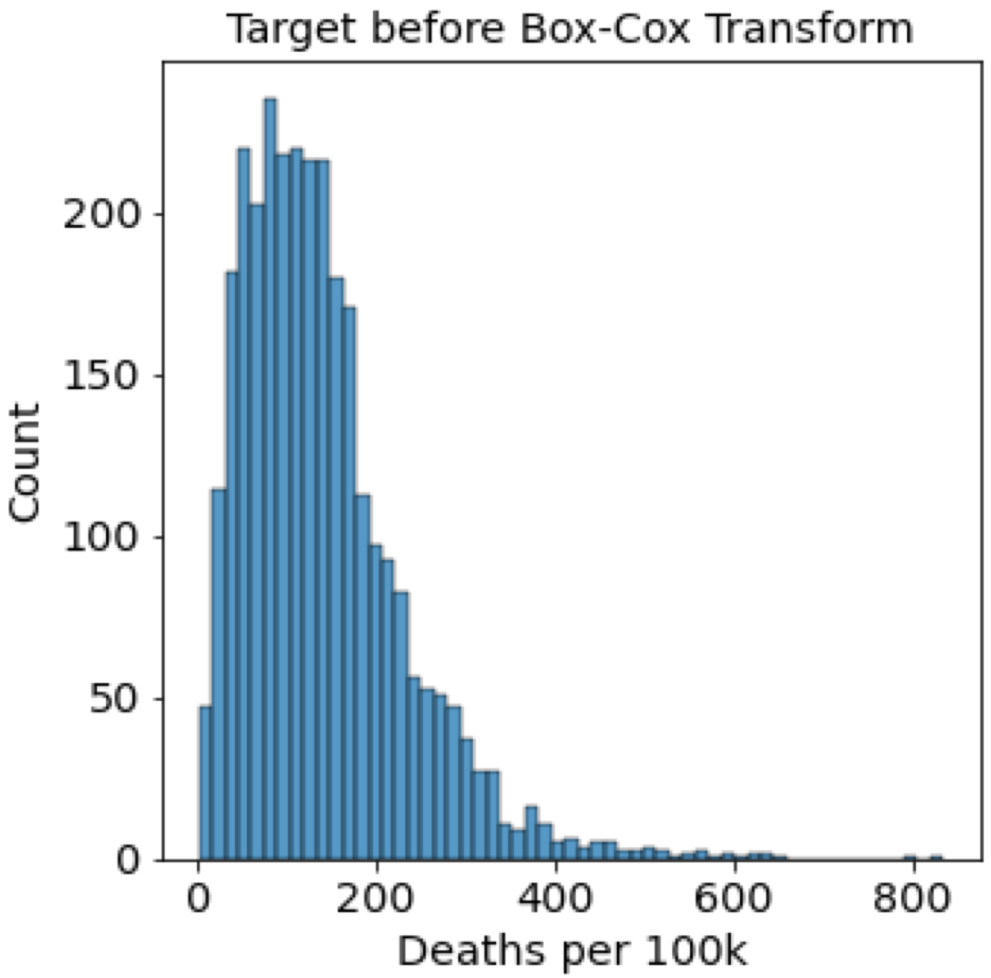
- 62 features consisting of various demographic and economic data

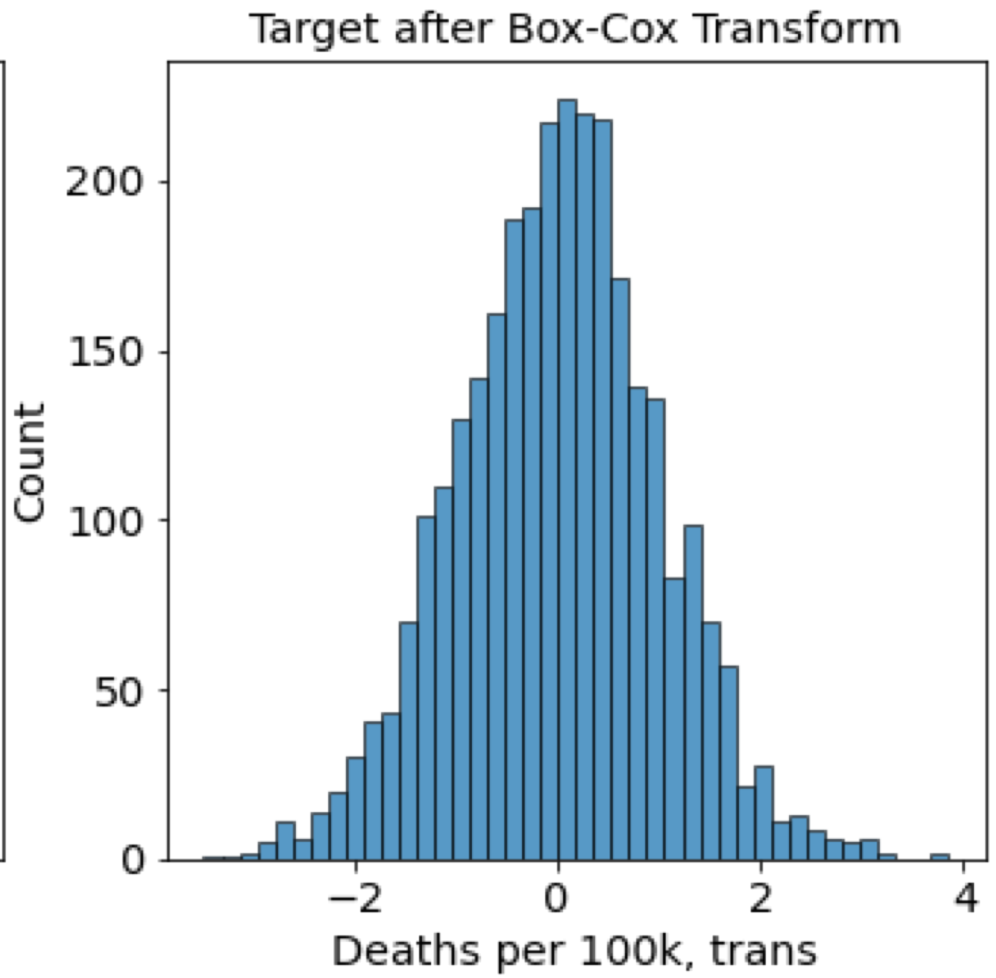
US County Cumulative Deaths per 100k People



Made using Plotly Choropleth Map. Blank counties are places where either my web-scraping failed, or I dropped outliers/entries with issues.

Target Distribution with and without Box-Cox Transform





- Transforming the target distribution to a normal shape was necessary for my regression to work consistently.

What influences the number of deaths?

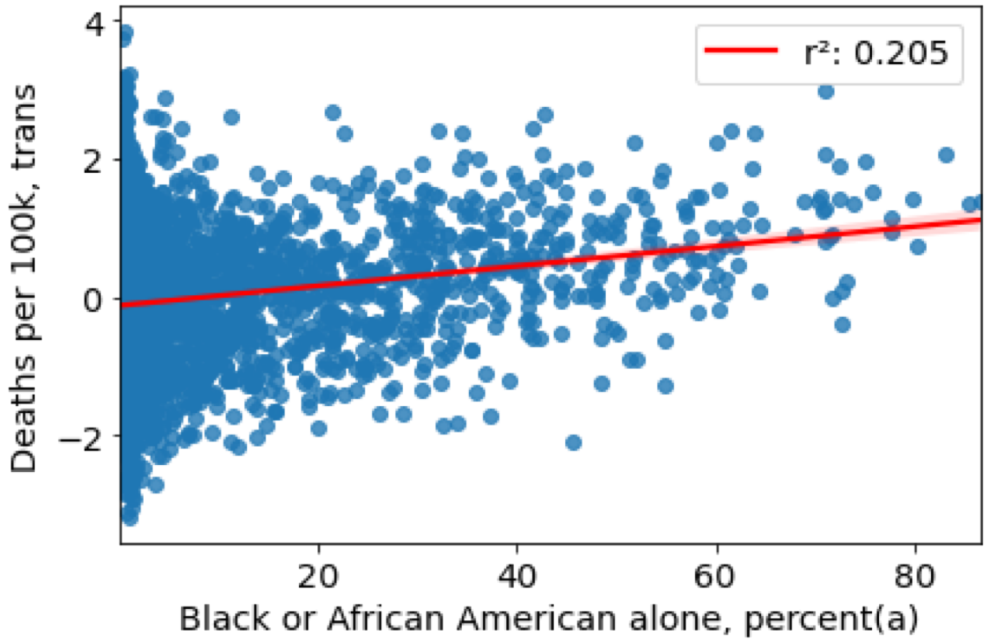
- Age
- Race
- Income
- Education
- Health care
- Etc.

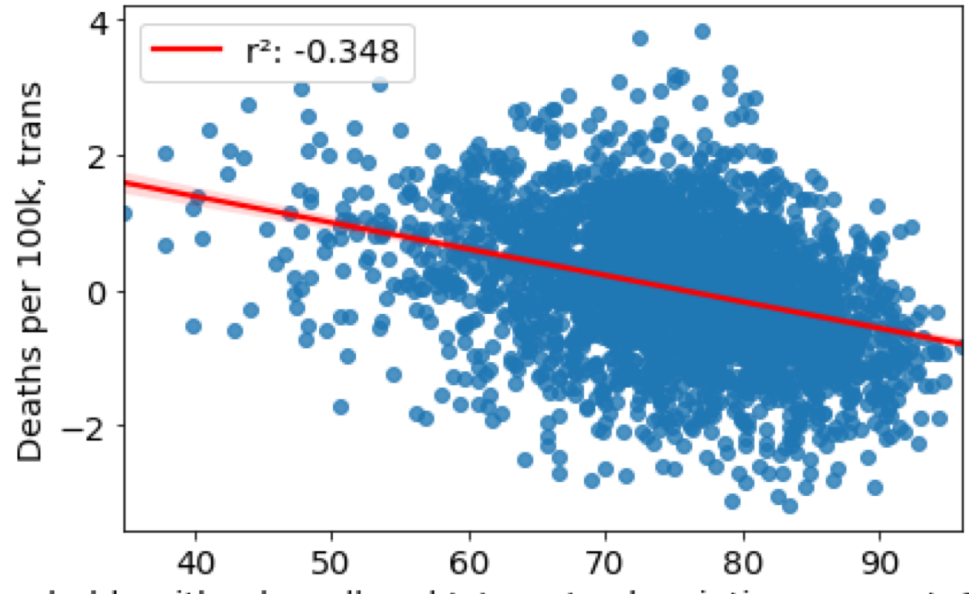
- A lot of these are significantly correlated to each other
- By trial and error I selected 12 features for my model

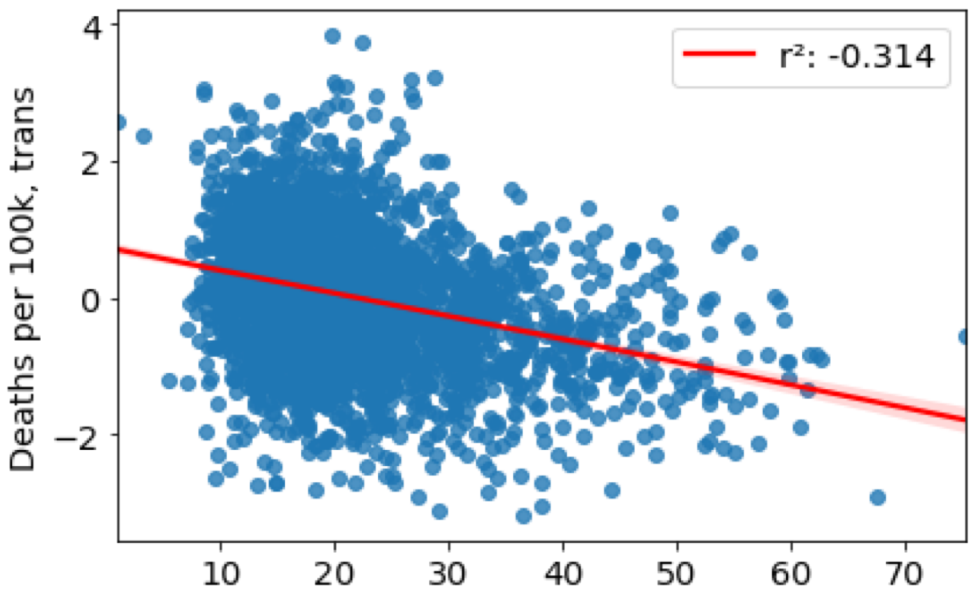
Selected Features

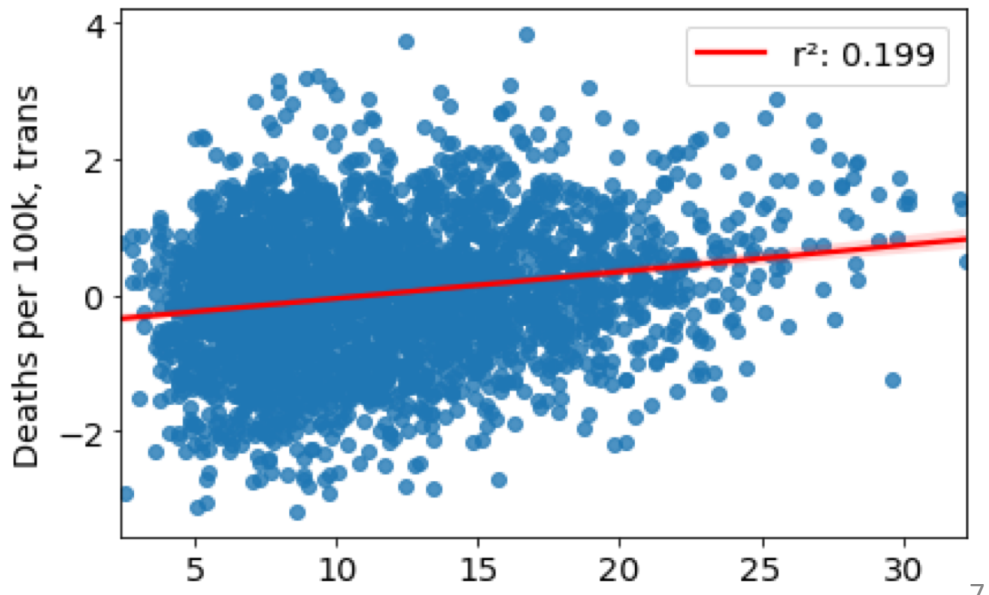
Race/Age
Income Related
Education/Information

Number	Features	Correlation to target
1	Persons 65 years and over, percent	0.047
2	Black or African American alone, percent	0.205
3	Two or More Races, percent	-0.278
4	White alone, not Hispanic or Latino, percent	-0.201
5	Persons without health insurance, under age 65 years, percent	0.199
6	Median value of owner-occupied housing units, 2015-2019	-0.369
7	Median household income (in 2019 dollars), 2015-2019	-0.289
8	Living in same house 1 year ago, percent of persons age 1 year+, 2015-2019	0.186
9	Households with a computer, percent, 2015-2019	-0.353
10	Households with a broadband Internet subscription, percent, 2015-2019	-0.348
11	High school graduate or higher, percent of persons age 25 years+, 2015-2019	-0.276
12	Bachelor's degree or higher, percent of persons age 25 years+, 2015-2019	-0.314


r²: 0.205
Deaths per 100k, trans
Black or African American alone, percent(a)


r²: -0.348
Deaths per 100k, trans
Households with a broadband Internet subscription, percent, 2015-2019

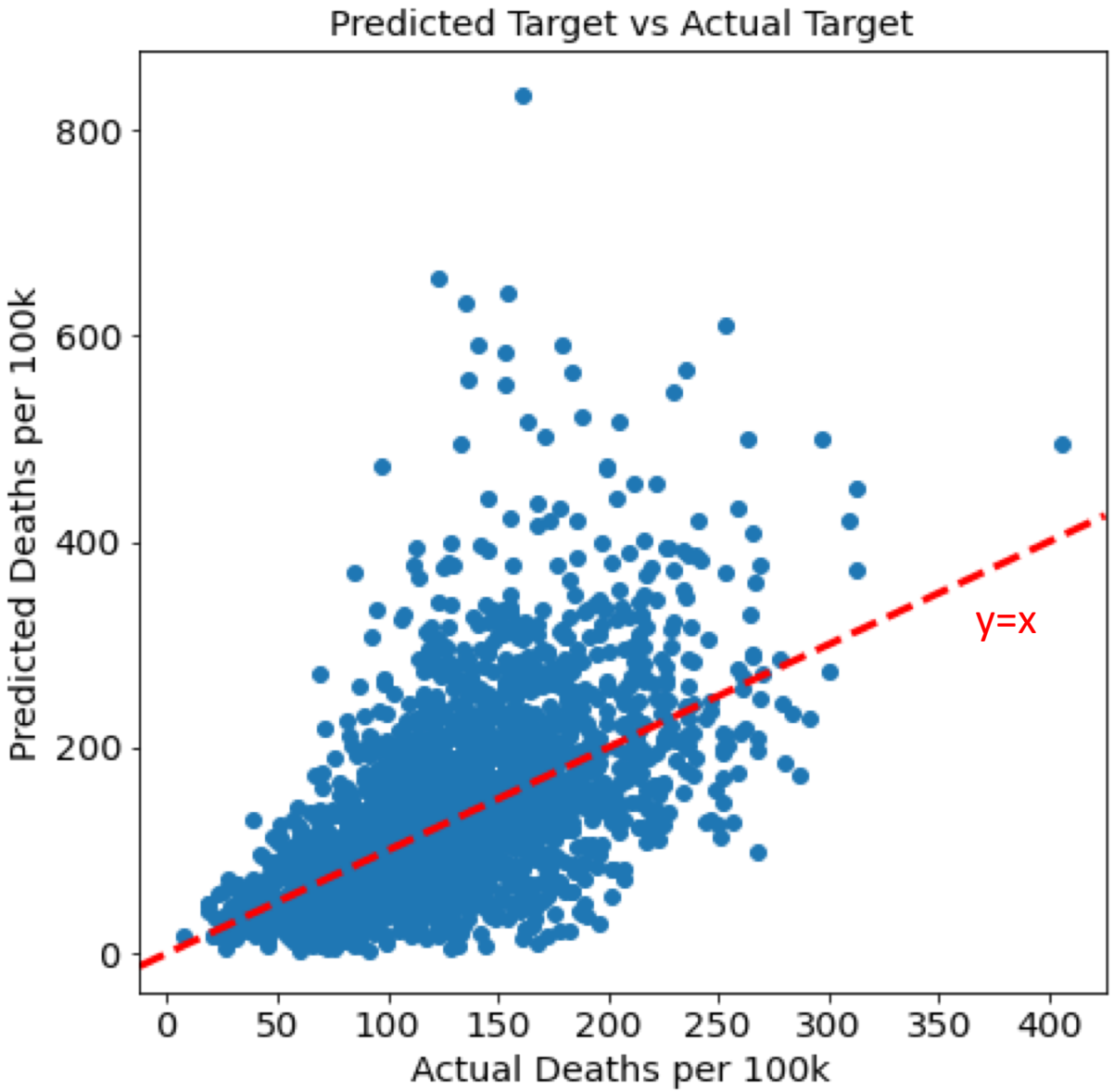

r²: -0.314
Deaths per 100k, trans
Bachelor's degree or higher, percent of persons age 25 years+, 2015-2019

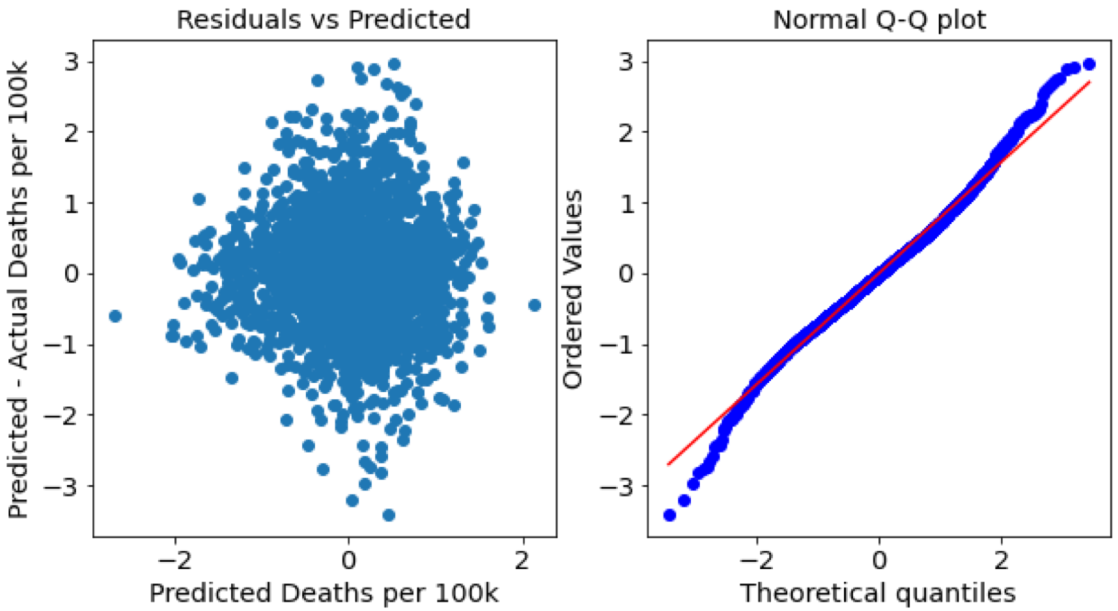

r²: 0.199
Deaths per 100k, trans
Persons without health insurance, under age 65 years, percent

Model Choice: Lasso with standard polynomial features

- Polynomial degree 2, including all poly features, not just interaction terms
- ƛ = 4e-4
- Ultimately I selected the model which performed the best, regardless of complexity
- I decided this because this was an analysis on life/death data, and every little bit matters

Model Performance

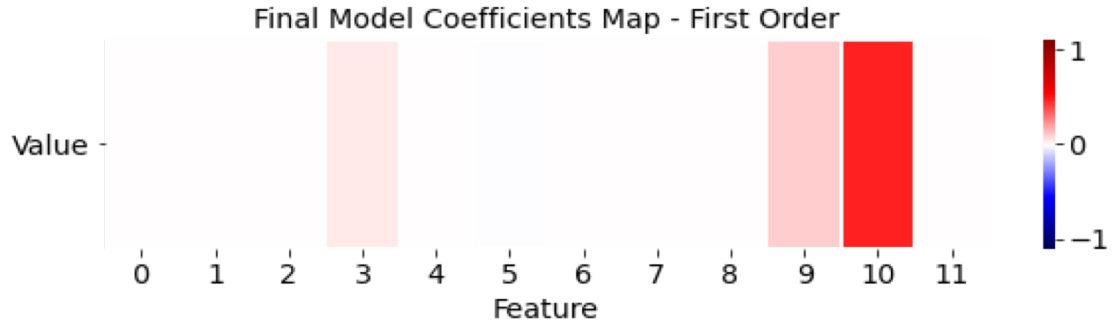


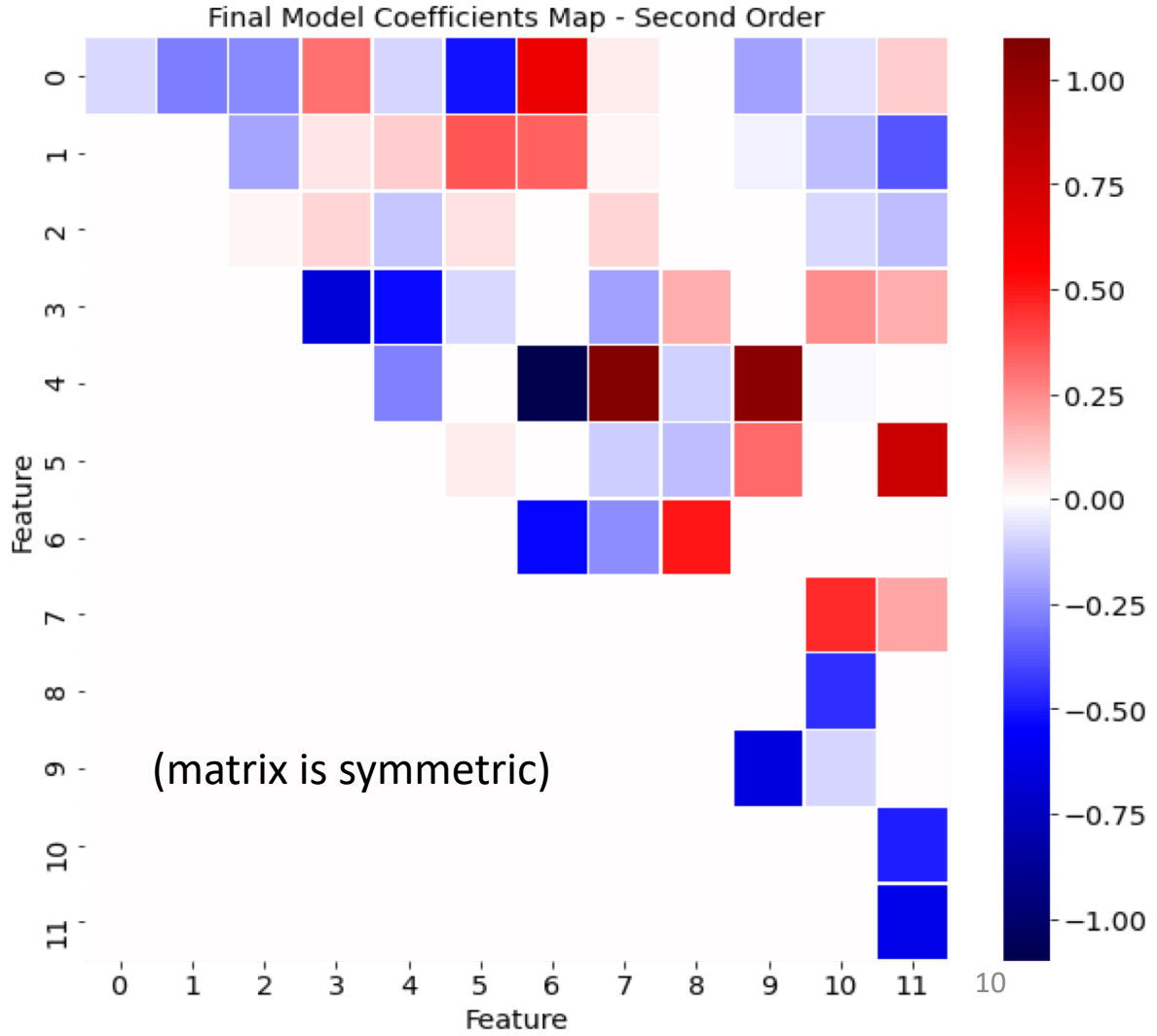


- The predicted vs actual plot shows that my model tends to overestimate the number of deaths
- Residuals are relatively happy
- Variance is high

Polynomial Coefficients

#	Feature
0	Persons 65 years and over, percent
1	Black or African American alone, percent
2	Two or More Races, percent
3	White alone, not Hispanic or Latino, percent
4	Median value of owner-occupied housing units, 2015-2019
5	Living in same house 1 year ago, percent of persons age 1 year+, 2015-2019
6	Households with a computer, percent, 2015-2019
7	Households with a broadband Internet subscription, percent, 2015-2019
8	High school graduate or higher, percent of persons age 25 years+, 2015-2019
9	Bachelor's degree or higher, percent of persons age 25 years+, 2015-2019
10	Median household income (in 2019 dollars), 2015-2019
11	Persons without health insurance, under age 65 years, percent





Final Model Results

- r^2 = 32% on the test data
  - The unexplained variance is high
  - I'm not surprised by this considering the complexity of the problem
- MAE = 182.1 Deaths per 100k
- RMSE = 205.5 Deaths per 100k

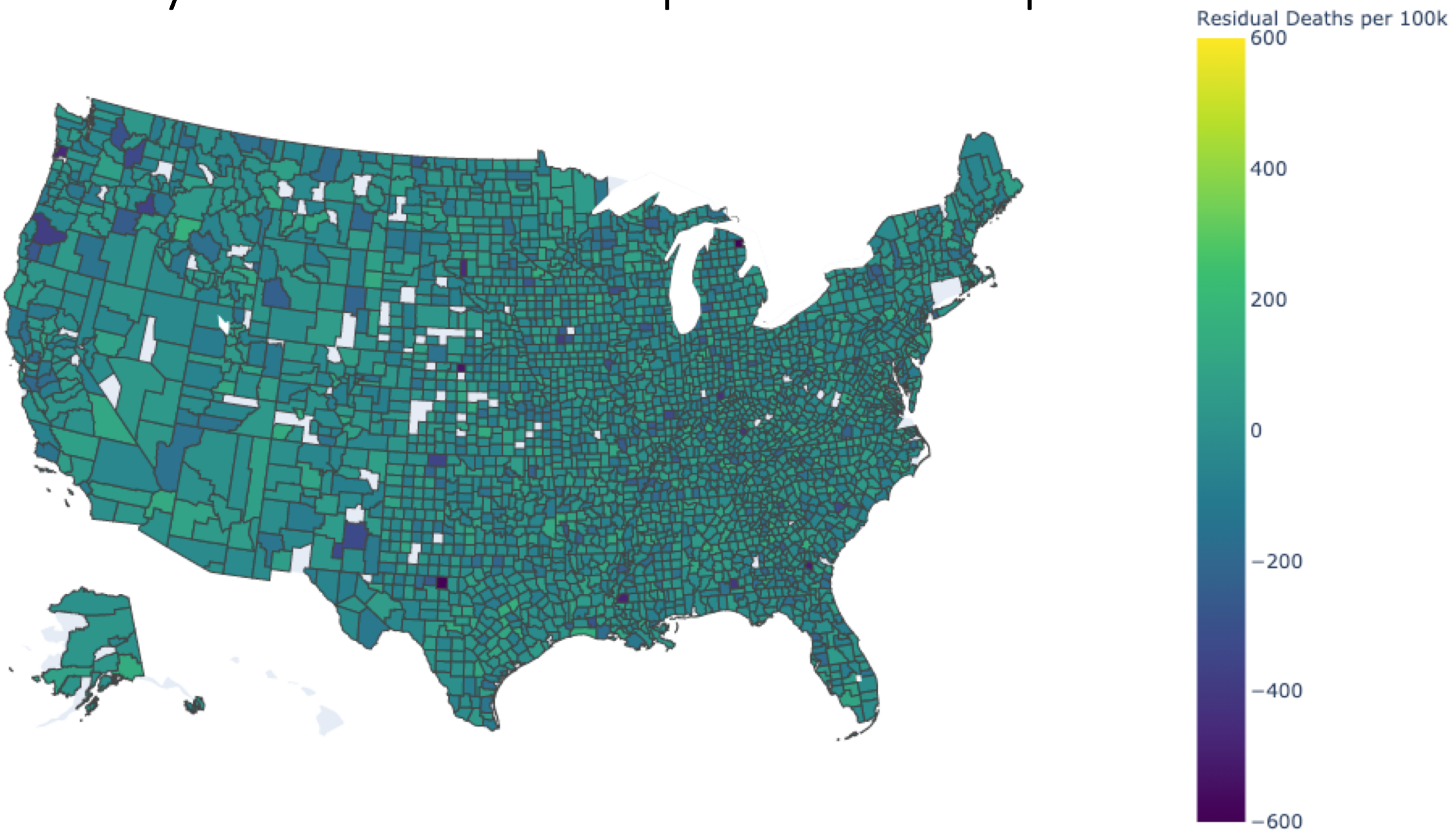
Future Work

- Ultimately the model would need to be improved significantly for it to be of any real use
  - More features including health care related statistics, time-dependent features, etc.
  - More sophisticated calculations on those features
  - Finer granularity: cities or census tracts
- This analysis workflow could be applied on other target variables entirely since census data is pretty general
  - Other diseases
  - Business focus

End - Questions?

Appendix

US County Residual Deaths per 100k People



Simpler Model – LassoCV with standard features

('Persons 65 years and over, percent', 0.074)
('Black or African American alone, percent(a)', -0.047)
('Two or More Races, percent', -0.228)
('White alone, not Hispanic or Latino, percent', -0.327)
('Median value of owner-occupied housing units, 2015-2019', -0.322)
('Living in same house 1 year ago, percent of persons age 1 year+, 2015-2019', 0.002)
('Households with a computer, percent, 2015-2019', -0.193)
('Households with a broadband Internet subscription, percent, 2015-2019', 0.019)
('High school graduate or higher, percent of persons age 25 years+, 2015-2019', 0.084)
("Bachelor's degree or higher, percent of persons age 25 years+, 2015-2019", -0.057)
('Persons without health insurance, under age 65 years, percent', 0.045)
('Median household income (in 2019 dollars), 2015-2019', 0.162)

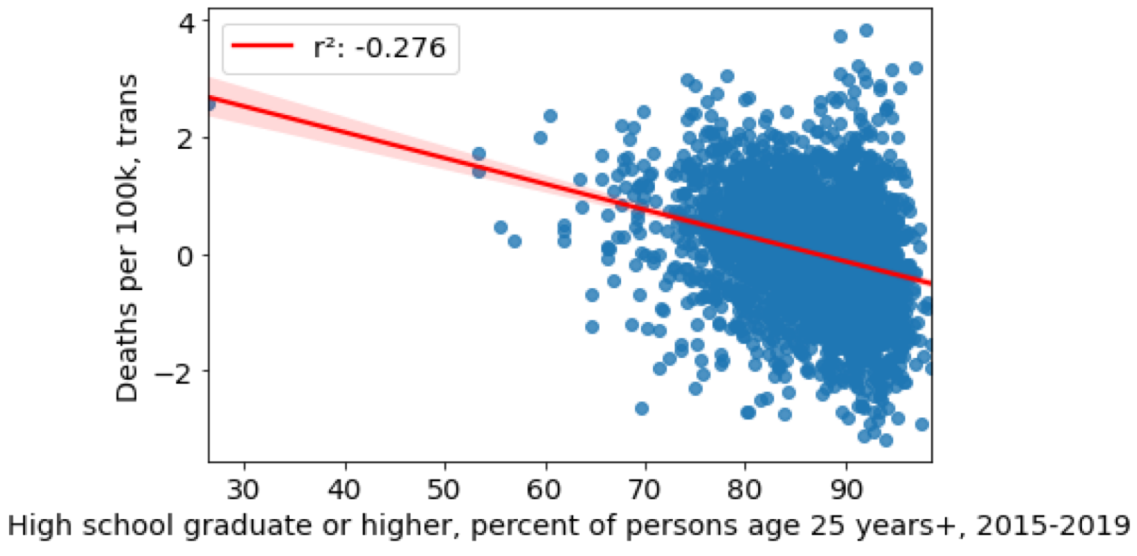
$\lambda = 0.0014$

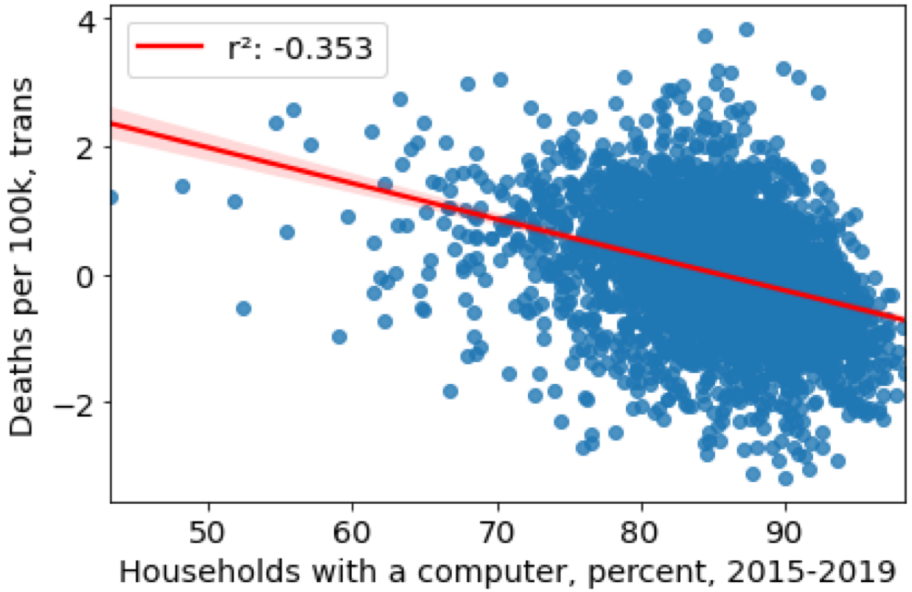
$r^2 = 27\%$
MAE = 188.2 Deaths per 100k
RMSE = 211.8 Deaths per 100k

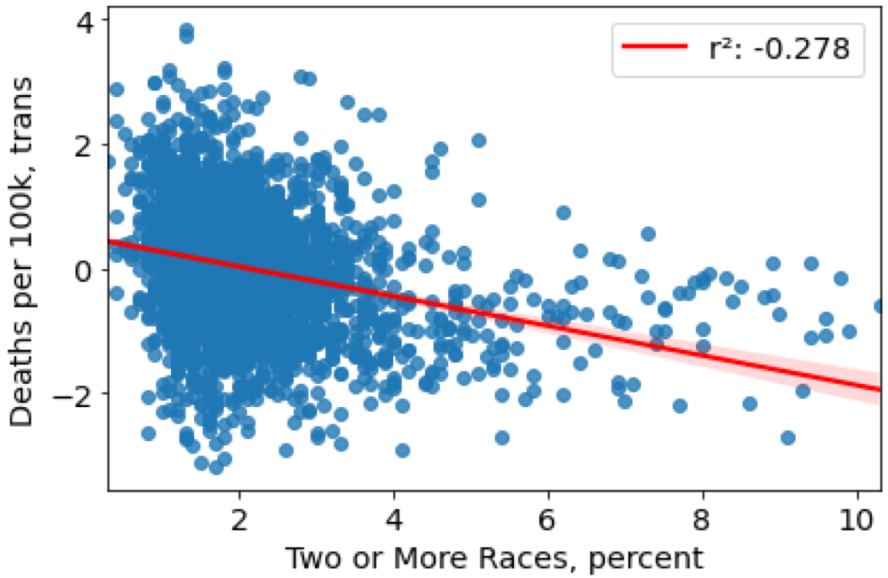
Model progression (on training data)

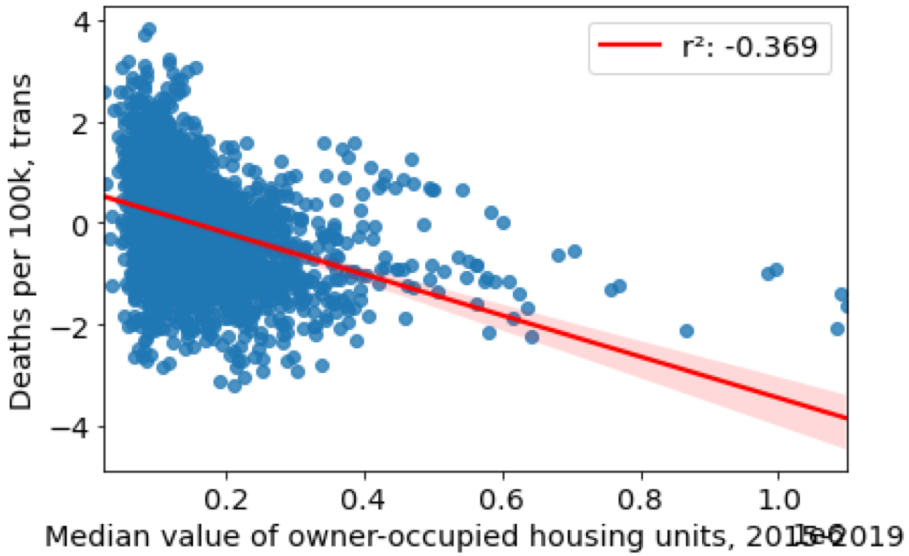
- ~0.1 with simple linear regression using most correlated features
- ~0.2 after reducing features manually
- ~0.27 after Box-Cox transform of target
- ~0.315 after poly transform of features
- ~0.36 using Lasso on poly features

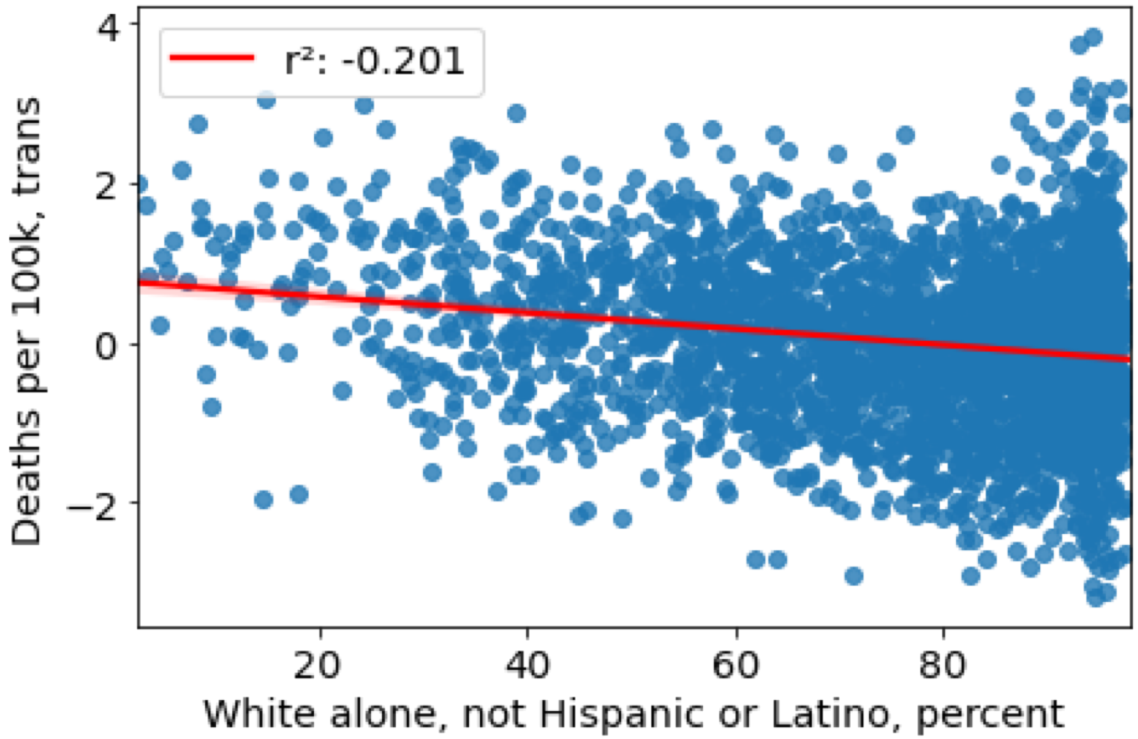
- Ridge and Lasso were basically equivalent
- I chose Lasso because it zeroed out a good amount of the polynomial features

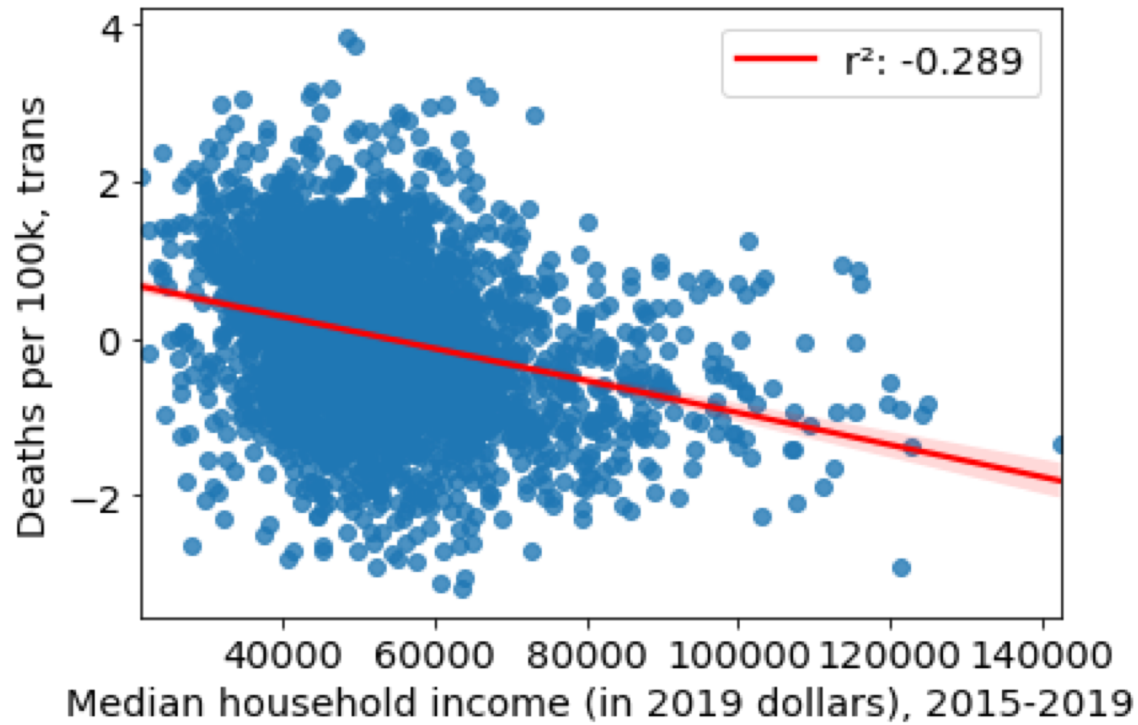

r²: -0.276
Deaths per 100k, trans
High school graduate or higher, percent of persons age 25 years+, 2015-2019


r²: -0.353
Deaths per 100k, trans
Households with a computer, percent, 2015-2019

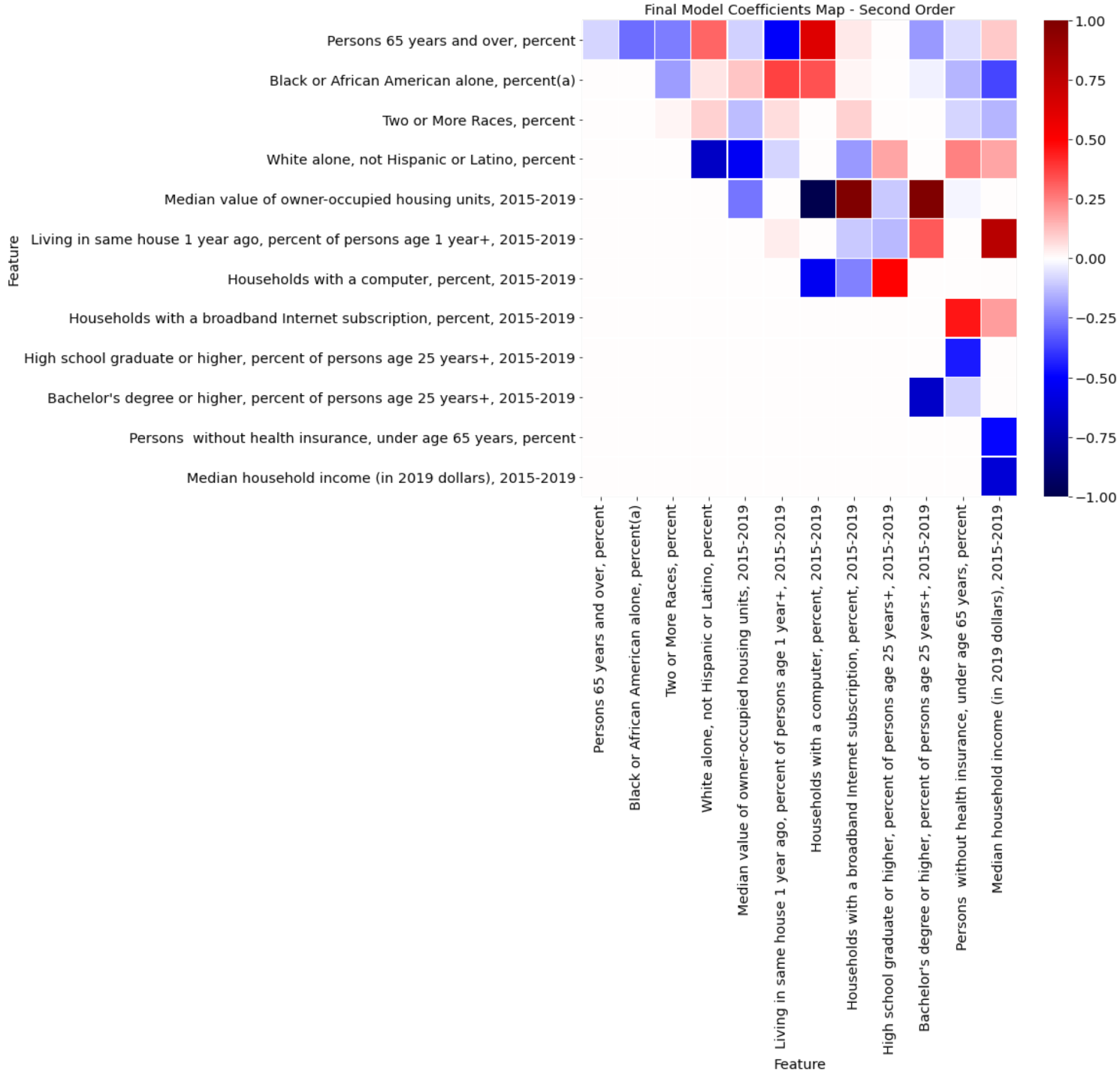

r²: -0.278
Deaths per 100k, trans
Two or More Races, percent


r²: -0.369
Deaths per 100k, trans
Median value of owner-occupied housing units, 2015-2019


r²: -0.201
Deaths per 100k, trans
4
2
0
−2
20
40
60
80
White alone, not Hispanic or Latino, percent


r²: -0.289
Deaths per 100k, trans
4
2
0
−2
40000
60000
80000
100000
120000
140000
Median household income (in 2019 dollars), 2015-2019

Final Model Coefficients Map - First Order
Value
Persons 65 years and over, percent
Black or African American alone, percent(a)
Two or More Races, percent
White alone, not Hispanic or Latino, percent
Median value of owner-occupied housing units, 2015-2019
Living in same house 1 year ago, percent of persons age 1 year+, 2015-2019
Households with a computer, percent, 2015-2019
Households with a broadband Internet subscription, percent, 2015-2019
High school graduate or higher, percent of persons age 25 years+, 2015-2019
Bachelor's degree or higher, percent of persons age 25 years+, 2015-2019
Persons without health insurance, under age 65 years, percent
Median household income (in 2019 dollars), 2015-2019
Feature
1
0
−1


Final Model Coefficients Map - Second Order
Feature
Persons 65 years and over, percent
Black or African American alone, percent(a)
Two or More Races, percent
White alone, not Hispanic or Latino, percent
Median value of owner-occupied housing units, 2015-2019
Living in same house 1 year ago, percent of persons age 1 year+, 2015-2019
Households with a computer, percent, 2015-2019
Households with a broadband Internet subscription, percent, 2015-2019
High school graduate or higher, percent of persons age 25 years+, 2015-2019
Bachelor's degree or higher, percent of persons age 25 years+, 2015-2019
Persons without health insurance, under age 65 years, percent
Median household income (in 2019 dollars), 2015-2019
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
Feature

Box-Cox Transform:

$$x_i^{(\lambda)} = \begin{cases} \dfrac{x_i^{\lambda} - 1}{\lambda} & \text{if } \lambda \neq 0, \\ \ln(x_i) & \text{if } \lambda = 0, \end{cases}$$