Understanding the impact of socio-economic factors on cancer mortality rates in South Dakota using variable selection techniques

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Outline

Introduction

- According the CDC, cancer was the second leading cause of death in 2020 [National Center for Health Statistics, 2020].
- There is a growing body of evidence that socio-economic (poverty, insurace status, *etc*,...) factors contribute the cancer mortality rates [National Cancer Institute, 2015].

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- There is a growing body of evidence that socio-economic (poverty, insurace status, *etc*,...) factors contribute the cancer mortality rates [National Cancer Institute, 2015].
- This study sought to understand how eight socio-economic and lifestyle factors impacted cancer mortality rates per 100,000 on a county level in South Dakota (SD).
- To do this, we considered several variable selection techniques to create a parsimonious model.

Data Sources

- **Cancer incidence** and **mortality** age-adjusted rates per 100,000 (2009-2018) were taken from the South Dakota Department of Health [South Dakota Cancer Registry, 2022].

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- **Obesity** percentage, **food index**, **smoking** percentage, and excessive **drinking** percentage were provided by the Counties Ranking and Roadmap site [County Health Rankings and Roadmaps, 2022].

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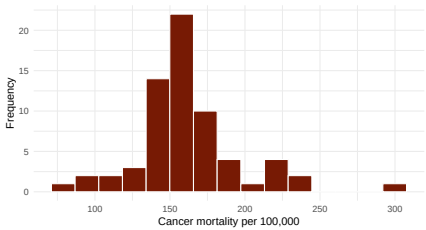
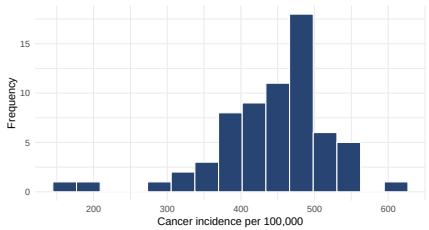
- All code and full data set are available at https://github.com/espors/cancer_mortality_modeling.

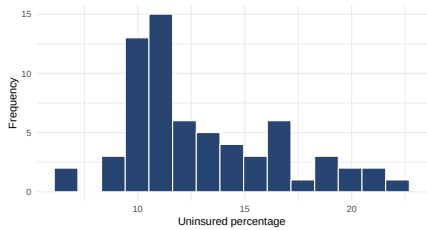
Exploratory Data Analysis I



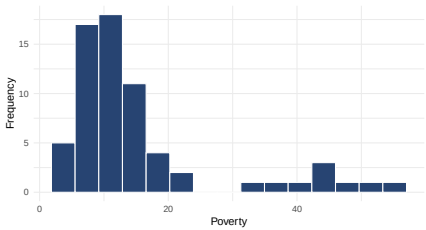
(a) Cancer mortality



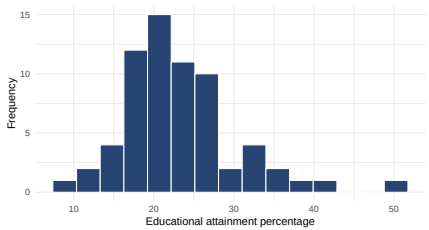
(b) Cancer incidence



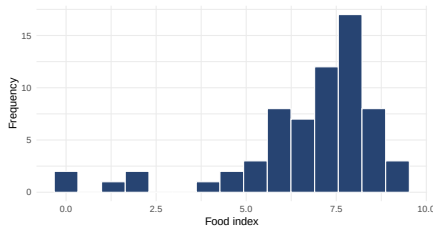
(c) Uninsured



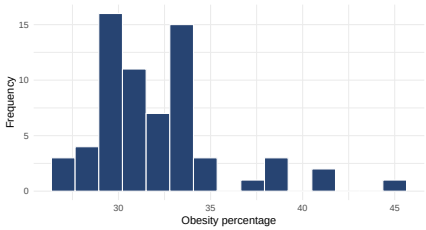
(d) Poverty percentage



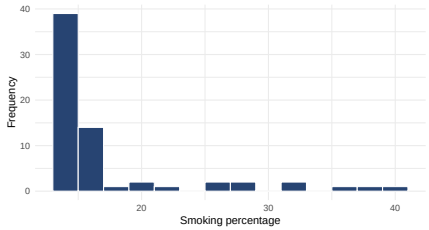
(e) Educational attainment



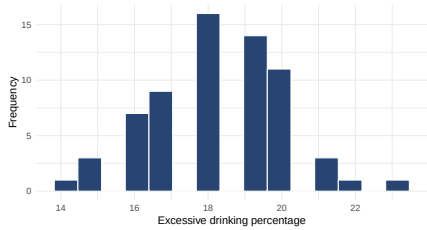
(f) Food index



(g) Obesity

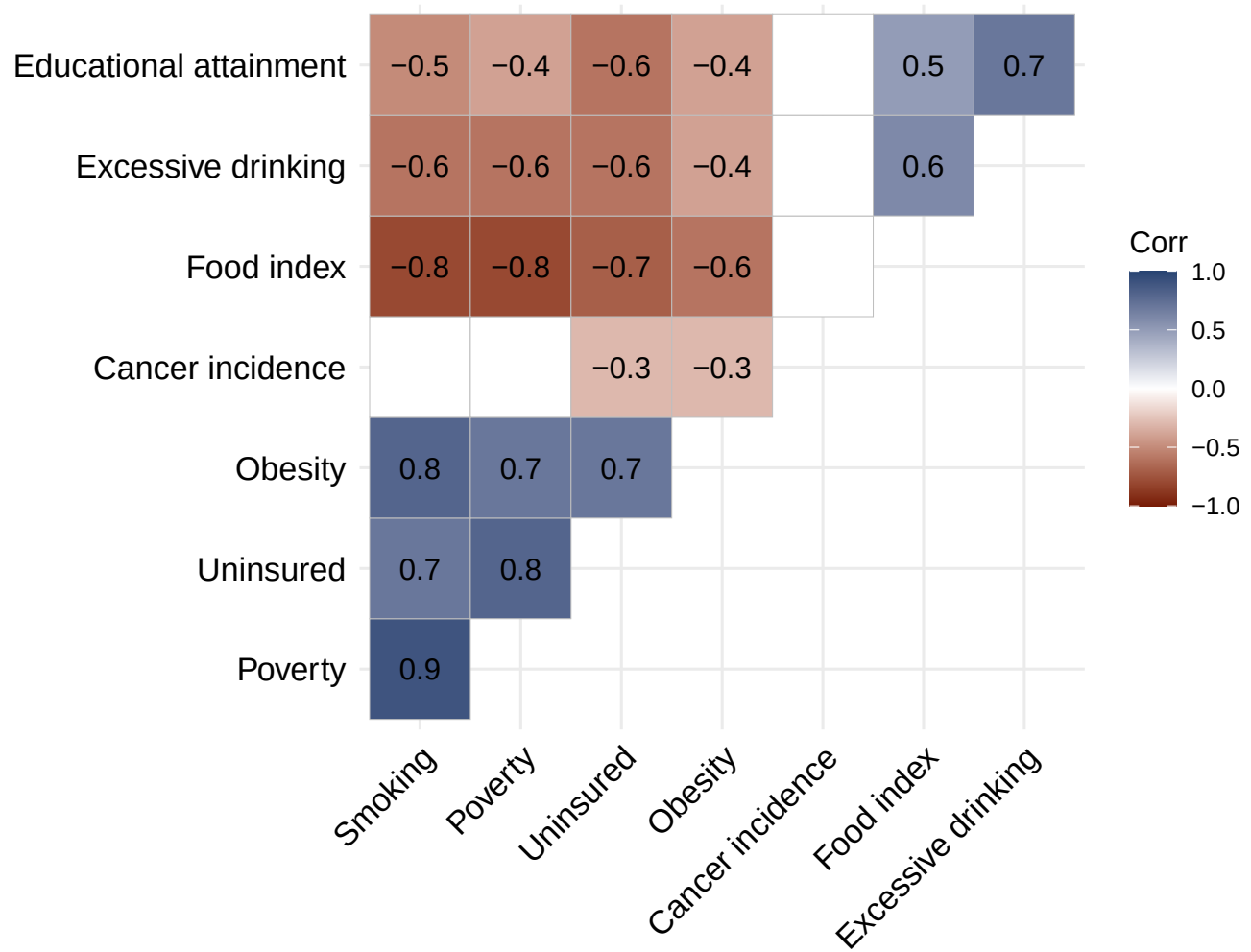


(h) Smoking



(i) Drinking

Exploratory Data Analysis II



Moran's I

- Moran's I was used to determine if the data was spatially uncorrelated, (preserve normality assumption)

$$I = \frac{N}{\mathbf{W}} \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{N}(x_i - \bar{x})^2} \tag{1}$$

- $\mathbf{W}$ is sum of the weight matrix W
- $w_{ij} \in 0, 1$ indicates the value in W
- N is number of elements, x is response variable, $-1 \leq I \leq 1$

Multiple Linear Regression

- To gain insight into the selected socio-economic predictor variables impacted moralities in SD's counties, a traditional multiple linear regression model was considered.
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- In matrix notation, the estimated regression model has the form $\hat{\boldsymbol{Y}} = \boldsymbol{X}\boldsymbol{b}$ where $\boldsymbol{b}$ is found with

$$\boldsymbol{b} = \arg\min_{\beta} \left\{ \sum_{i=1}^{66} \left(Y_i - \beta_0 - \sum_{j=1}^{p-1} \beta_j x_{ij} \right)^2 \right\} \tag{2}$$

Variable Selection Techniques I

- **Stepwise regression** is a feature selection technique that iteratively adds and drops predictor variables in a succession of models and selects the model with predictors that has the smallest AIC value.

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$$\boldsymbol{b} = \arg\min_{\beta} \left\{ \sum_{i=1}^{66} \left(Y_i - \beta_0 - \sum_{j=1}^{p-1} \beta_j x_{ij} \right)^2 + \lambda \sum_{j=1}^{p-1} \beta_j^2 \right\}.$$

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  - **Lasso regression** (least operate shrinkage & selection operator) adds an 'L_1' penalty such that $\boldsymbol{b}$ is found with

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Variable Selection Techniques

- **Elastic net regression** combines the best of ridge and lasso regression and $\boldsymbol{b}$ is found with

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or

$$\boldsymbol{b} = \arg\min_{\beta} \left\{ \sum_{i=1}^{66} \left(Y_i - \beta_0 - \sum_{j=1}^{p-1} \beta_j x_{ij} \right)^2 + \alpha \sum_{j=1}^{p-1} \beta_j^2 + (1-\alpha) \sum_{j=1}^{p-1} |\beta_j| \right\}$$

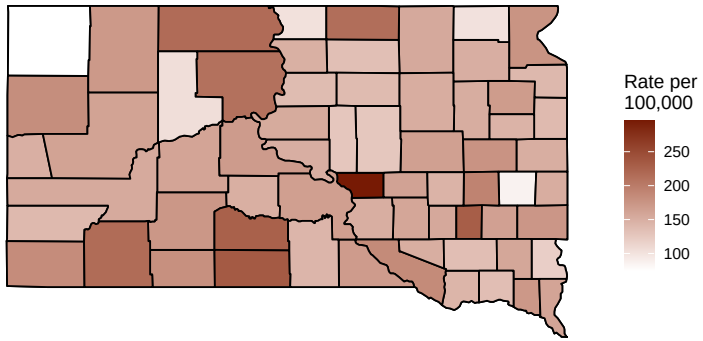
where $\alpha = \frac{\lambda_2}{\lambda_2 + \lambda_1} \in [0, 1)$.

- Predictions*

Moran's I

- Statistics calculated for Moran's I Mortality rate per 100,000.

Statistic	Value
Mean Response	160.4379
Moran's I	-0.0678
E[I]	-0.0152
Variance	0.0214
W	348
Z	-0.3584
p	0.3632



$$Z = \frac{E[I] - I}{\sqrt{v}} \approx -0.36 \implies p = 0.36 \geq 0.05 \tag{3}$$

- Fail to reject H_0 : no spatial correlation

Regression Models

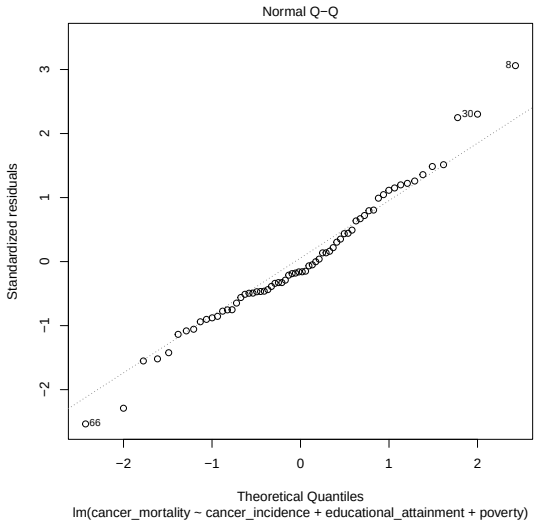
Summary of the regression models including the estimated coefficients, t-value, p-value, and adjusted R-squared.

	Model 1 - Full			**Model 2 - No Smoking**		
Variables	Coeff	t-value	$\Pr(>\|t\|)$	Coeff	t-value	$\Pr(>\|t\|)$
Cancer Incidence (Rate)	0.188	4.675	$1.84 \cdot 10^{-5}$	0.188	4.555	$2.74 \cdot 10^{-5}$
Obesity (%)	−2.44	−1.719	0.0911	−1.32	−0.995	0.323
Education Attainment (%)	−1.709	−2.607	0.011	−2.058	−3.185	0.002
Poverty (%)	0.931	1.242	0.219	2.038	4.024	0.0002
Uninsured (%)	−0.623	−0.407	0.685	−1.178	−0.763	0.448
Food Index	0.237	0.093	0.926	−1.359	−0.549	0.585
Drinking (%)	3.44	1.303	0.197	4.23	1.586	0.118
Smoking (%)	2.90	1.964	0.054	–	–	–
	Adj. R-sqr: 0.567, Mean VIF: 4.07			Adj. R-sqr: 0.546, Mean VIF: 2.30		

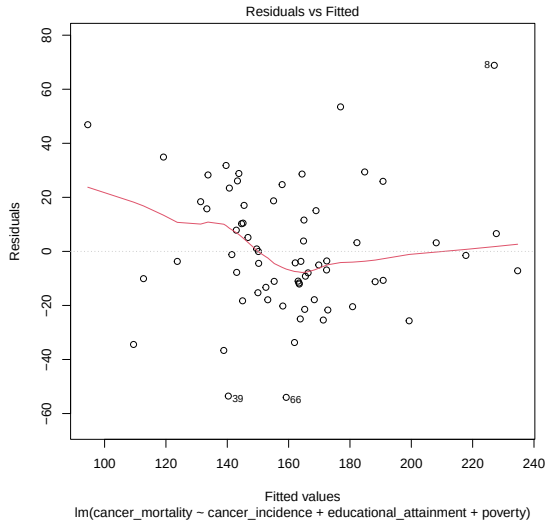
	Model 3 - Stepwise			**Model 4 - Penalized**		
Variables	Coeff	t-value	$\Pr(>\|t\|)$	Coeff	t-value	$\Pr(>\|t\|)$
Cancer Incidence (Rate)	0.204	5.205	$2.41 \cdot 10^{-6}$	0.210	5.298	$1.7 \cdot 10^{-6}$
Education Attainment (%)	−1.799	−3.130	0.002	−1.268	−2.492	0.015
Poverty (%)	1.716	5.673	$4.11 \cdot 10^{-7}$	1.457	1.242	0.00034
Food Index	–	–	–	−0.599	−0.243	0.808
Drinking (%)	3.787	1.479	0.144	–	–	–
	Adj. R-sqr: 0.554, Mean VIF: 1.71			Adj. R-sqr: 0.538, Mean VIF: 1.93		

Regression Models

	Model 5 - Reduced		
Variables	Coeff	t-value	$\Pr(>\|t\|)$
Cancer Incidence (Rate)	0.21	5.333	$1.44 \cdot 10^{-6}$
Educational Attainment (%)	-1.310	-2.760	0.007
Poverty (%)	1.522	5.530	$6.82 \cdot 10^{-7}$
	Adj. R-sqr: 0.545, Mean VIF: 1.30		



(j) Q-Q Plot



(k) Residual vs Fitted

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- Cancer incidence was positively associated with cancer mortality. In Model 5, for an additional case per 100,000, there was an additional 0.21 deaths per 100,000.
- Poverty percentage was positively associated with cancer mortality. For an one percent increase in a county's poverty percentage, there was an additional 1.52 cancer-deaths per 100,000.
  - Persistent poverty is strongly associated with increased cancer mortality rates [Moss et al., 2020].
  - Eleven counties in SD are designated as experiencing persistent poverty.

Discussion

- Educational attainment was negatively associated with cancer mortality. For an additional percentage in educational attainment, there were a decrease of 1.31 deaths per 100,000.
  - There is less literature on education and cancer mortality, but one study did find a relationship between those who didn't finish high school and mortality [Barcelo et al., 2021].
  - There is emerging evidence on the relationship between education and general health [Zajacova and Lawrence, 2018].

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- **Limitations:** Much of the data was based on self-reported surveys and the residuals indicate that not all of the linear assumptions may have been met.
- **Future work:** The data analysis could be expanded to include non-parametric and clustering models.

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