Statistical Machine Learning Techniques for Predicting Lung Cancer Prevalence

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Introduction

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Motivation: To learn the underlying factors contributing to lung cancer prevalence

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Goal: To identify key features associated with lung cancer incidence

Data overview: Lung Cancer in Virginia (2014-2018)

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Table: General overview of study features, with the underlying population being individuals aged 18 and over

Group	**Features**	**Source**
Demographics	% Male, % Female, % Black, % White, % Hispanic, % Age $\geq$65	US Census ACS
Behavioral	Prevalence of Smoking, Binge Drinking, and Obesity	CDC PLACES
Socioeconomic	% Below Poverty, Social Deprivation Index (SDI)	US Census, Graham Center
Environmental	PM2.5 Air Quality (μg/m^3)	EPA Downscaler

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Unobserved or missing values are removed, as there is no clear rationale for imputation

Statistical machine learning techniques

Model formulation: Let Y_i denote the number of lung cancer cases in a population of size N_i

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We model Y_i using Poisson distribution given by

$$P(Y_i = y_i) = \frac{(N_i\lambda_i)^{y_i} e^{-N_i\lambda_i}}{y_i!},\ i = 1, 2, \cdots, n$$

Poisson generalized linear model: We model the incidence rate λ_i as $\lambda_i = \exp(\mathbf{x}_i^\top \boldsymbol{\beta})$

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Using the data $y_1, y_2, \ldots, y_n$, the objective function with elastic net regularization can be given by

$$\mathcal{L}(\boldsymbol{\beta}) = -\sum_{i=1}^{n} \left[y_i \log N_i + y_i \mathbf{x}_i^\top \boldsymbol{\beta} - N_i e^{\mathbf{x}_i^\top \boldsymbol{\beta}} - \log(y_i!) \right] + \alpha \left[\gamma \|\boldsymbol{\beta}\|_1 + \frac{1-\gamma}{2} \|\boldsymbol{\beta}\|_2^2 \right], \quad \alpha \geq 0, \ \gamma \geq 0$$

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We use this regularization approach to select features that are associated with the lung cancer incidence rate

XGBoost with Poisson Loss Function: We model the rate λ_i using tree at t-th iteration as $\log(\lambda_i) = f(\mathbf{x}_i, \eta_t)$, which is parameterized by η_t

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We use this approach to assess the importance of the selected variables in lung cancer incidence

Results of the study

Data splitting: Training data (70%) and testing data (30%)

Poisson generalized linear model

Hyperparameter selection:
Five-fold cross-validation on training data

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Evaluation metric: Mean Absolute Error (MAE)

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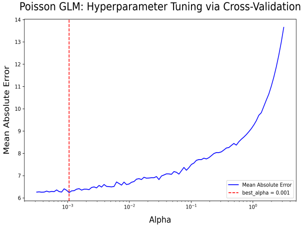

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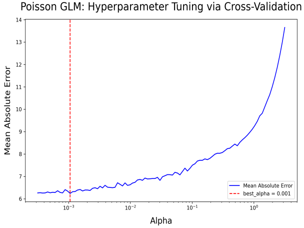
Elastic Net: Selected features



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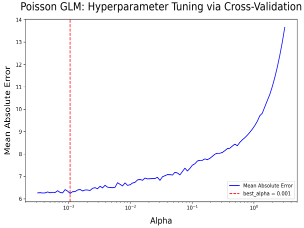

Table 1: Selected Features Using Elastic Net Regularization

Features	Parameter estimates
Pct_BelowPoverty_18andOver	-1.339
Pct_Population_Male_65andOver	2.797
Pct_Population_Female_65andOver	2.743
Pct_Black_Female_65andOver	2.487
Pct_White_65andOver	0.136
Pct_White_Male_65andOver	-0.484
Pct_Hisp_65andOver	-0.885
Pct_Hisp_Female_65andOver	-1.819
BINGE_CrudePrev	-0.017
CSMOKING_CrudePrev	0.125
OBESITY_CrudePrev	0.039
Median_Household_Income	-0.087
ZCTA_pm2_5	-0.069
sdi_score	0.034
Pct_White_Male_Between18and65	1.086
Pct_White_Female_Between18and65	1.296
Pct_Black_Female_Between18and65	1.434
Pct_Hisp_Male_Between18and65	-0.328
Pct_Hisp_Female_Between18and65	-1.263

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Learning rate tuning: It is tuned using cross-validation

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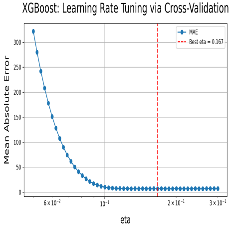

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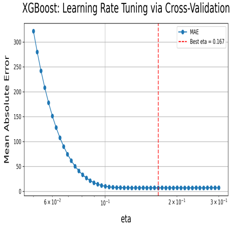
Gain index: Feature with high gain improves the model performance



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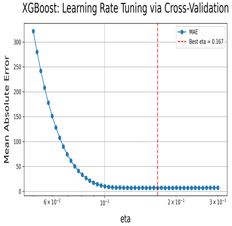
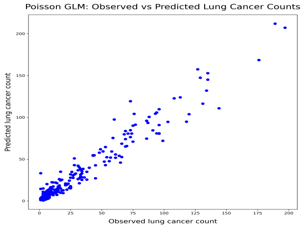


Table 2: Gain-based Feature Importance

Feature	Importance
Median_Household_Income	26.08
ZCTA_pm2_5	6.787
OBESITY_CrudePrev	5.602
Pct_Population_Female_65andOver	4.88
Pct_Hisp_Female_Between18and65	4.859
CSMOKING_CrudePrev	2.414
BINGE_CrudePrev	1.775
Pct_Population_Male_65andOver	1.69
Pct_Hisp_Female_65andOver	1.47
sdi_score	1.31
Pct_White_Male_Between18and65	1.205
Pct_White_65andOver	1.193
Pct_White_Male_65andOver	1.19
Pct_Hisp_65andOver	1.166
Pct_Black_Female_Between18and65	1.122
Pct_White_Female_Between18and65	1.108
Pct_Black_Female_65andOver	1.061
Pct_Hisp_Male_Between18and65	0.992
Pct_BelowPoverty_18andOver	0.399

Model performance on test data

Poisson generalized linear model



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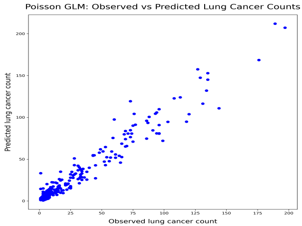
Mean absolute error: 6.313



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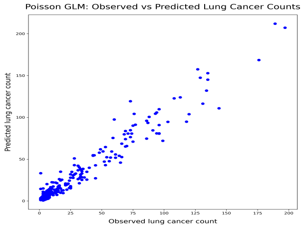

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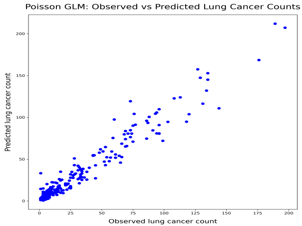

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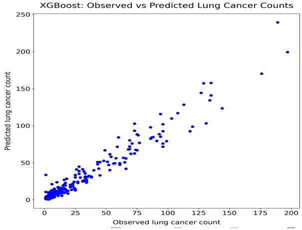

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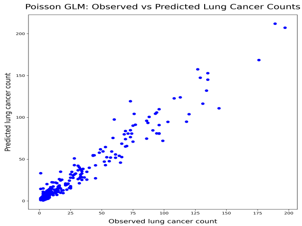

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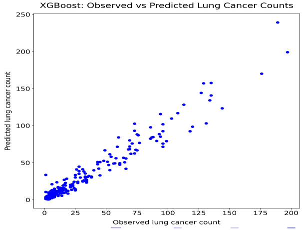

XGBoost

Mean absolute error: 5.963

Conclusion

Interpretation should be made with caution, as it reflects associations in the presence of other included features

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Smoking is positively associated while Income and PM2.5 are modestly negatively associated

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XGBoost improved prediction accuracy by 5.54% compared to the Poisson Generalized linear model

That concludes our presentation

Thank you for your attention!