Change in Local Healthy Food Retail Environment through Interactions in Population, Race and Nativity

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Population Association of America
Annual Meeting 2015

Healthy Food Environment Matters

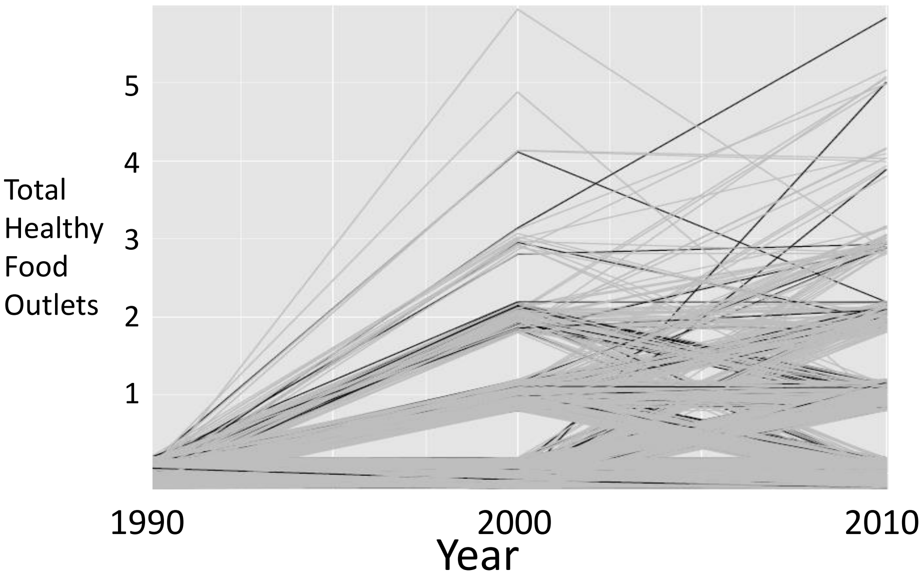
- Local characteristics and demographics are associated with presence of healthy food retail outlets. Foreign born populations have been associated with greater commercial resources including grocery stores.

Healthy food outlets = {large supermarkets, fruit & vegetable markets, natural food markets & nut stores, fish markets}

A Goal of Explaining Local Change

- How are local characteristics linked to change over time?
- Gain insight into processes leading to disparities.

Healthy Food Outlet Count across Decades for Tracts without Outlets in 1990



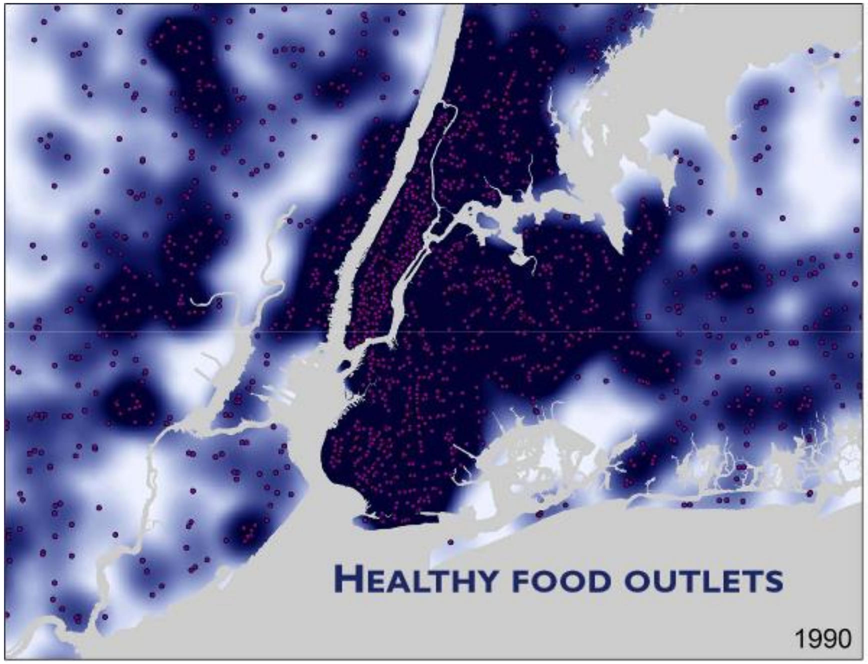
Business Data

National Establishment Time Series (NETS)

- Longitudinal ‘census of U.S. businesses’
- Geocoded to addresses and zip code
- 8 digit SIC code classifications
- 21 years of data
- 23 counties in NYC metropolitan area

Dependent Variable:

- Indicator for whether the was an increase in healthy food outlets.



Prepared by Danny Sheehan

Population Data and Tracts

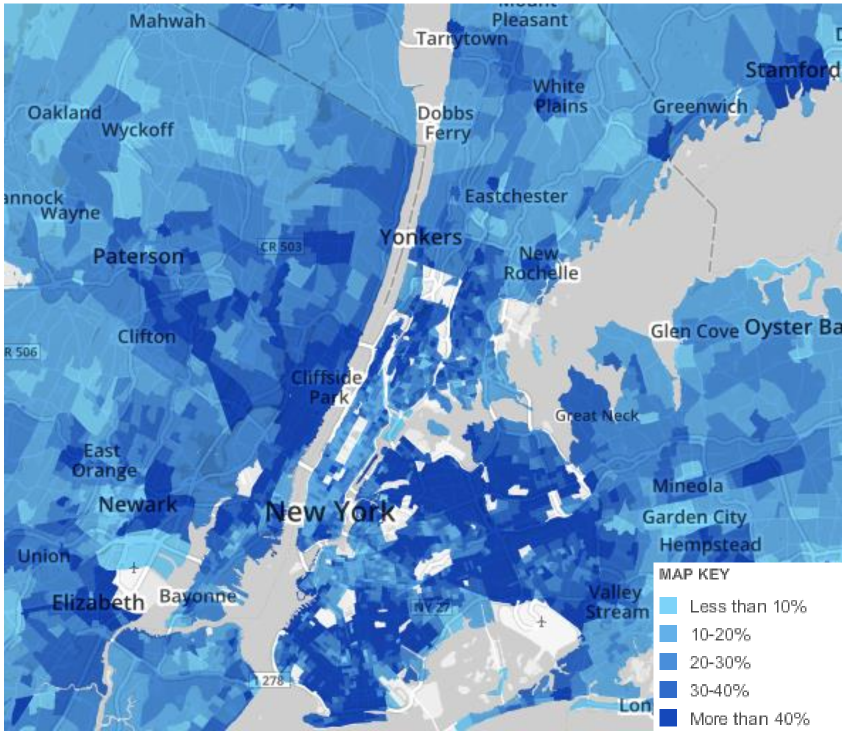
Population:

- U.S. Census
  - Decennial Census (1990, 2000, 2010)
  - American Community Survey (2007-2010)
- Geographic size
- Geographic adjacency

Explanatory Variables:

- Median Income
- % Poverty
- % Foreign Born
- % Non-Hispanic Black
- % Hispanic
- % Asian
- Total Population
- Census Tract Geographic Size

% Foreign Born Population



Derived Variables

Change in Tract Characteristics

$$\nabla\%ForeignBorn_{i,t_n} = \%ForeignBorn_{t_n} - \%ForeignBorn_{t_{n-1}}$$

Adjacent Tract Characteristic

$$\%ForeignBorn\_Adjacent_{i,t_n} = \frac{\sum_j^{N(i)} \%Poverty_{j,t_n} * Population_{j,t_n}}{\sum_j^{N(i)} Population_{j,t_n}}$$

Adjacent Tract **Change**

$$\nabla\%ForeignBorn\_Adjacent_{i,t_n} = \frac{\sum_j^{N(i)} \nabla\%\ Poverty_{j,t_n} * Population_{j,t_n}}{\sum_j^{N(i)} Population_{j,t_n}}$$

www.armellecaron.fr/works/les-villes-rangees/

Conceptualizing the Model

$$
\begin{aligned}
\mathit{Change\ in\ HealthyFoodOutlets} = {} & \%\mathit{ForeignBorn} + \\
& \%\mathit{ForeignBorn\_Change} + \\
& \%\mathit{ForeignBorn\_Adjacent} + \\
& \%\mathit{ForeignBorn\_Adjacent\_Change} + \ldots
\end{aligned}
$$

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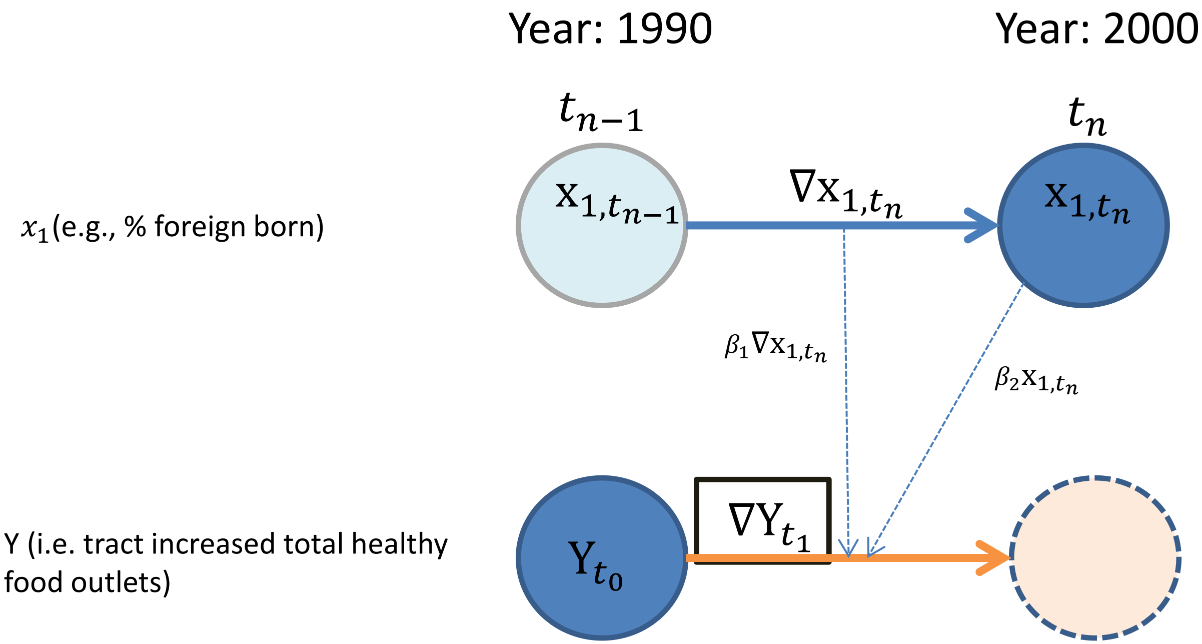
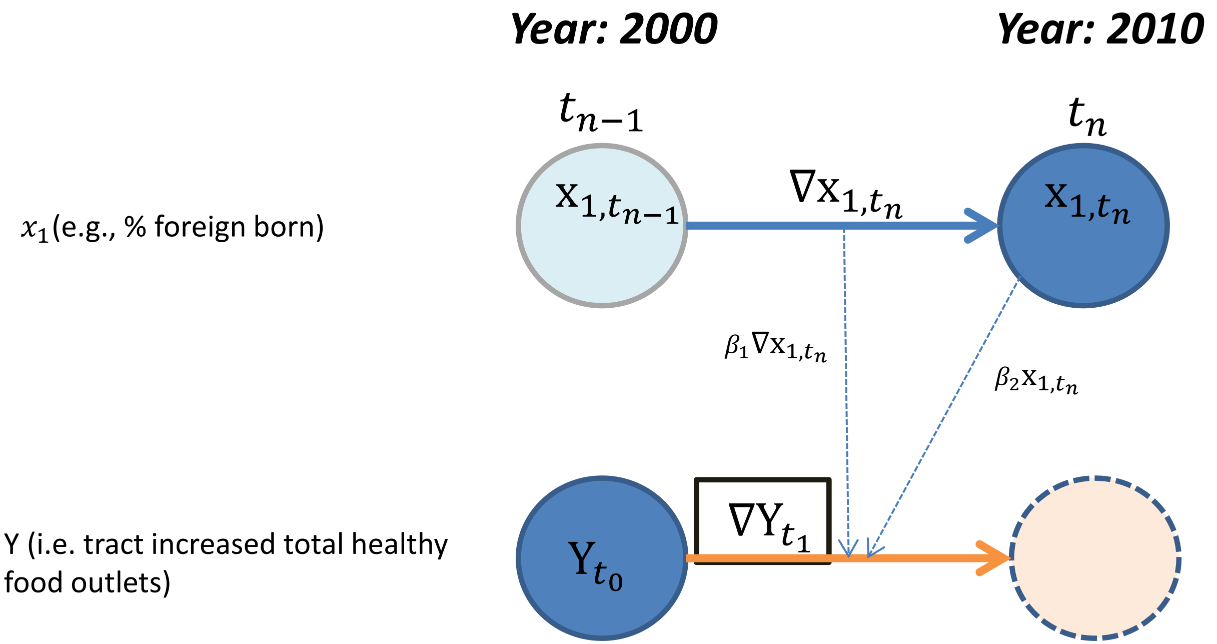


Conceptualizing the Model

Change in HealthyFoodOutlets = *%ForeignBorn* +
%ForeignBorn_Change +
%ForeignBorn_Adjacent +
%ForeignBorn_Adjacent_Change + …



Year: 2000

Year: 2010

t_{n-1}

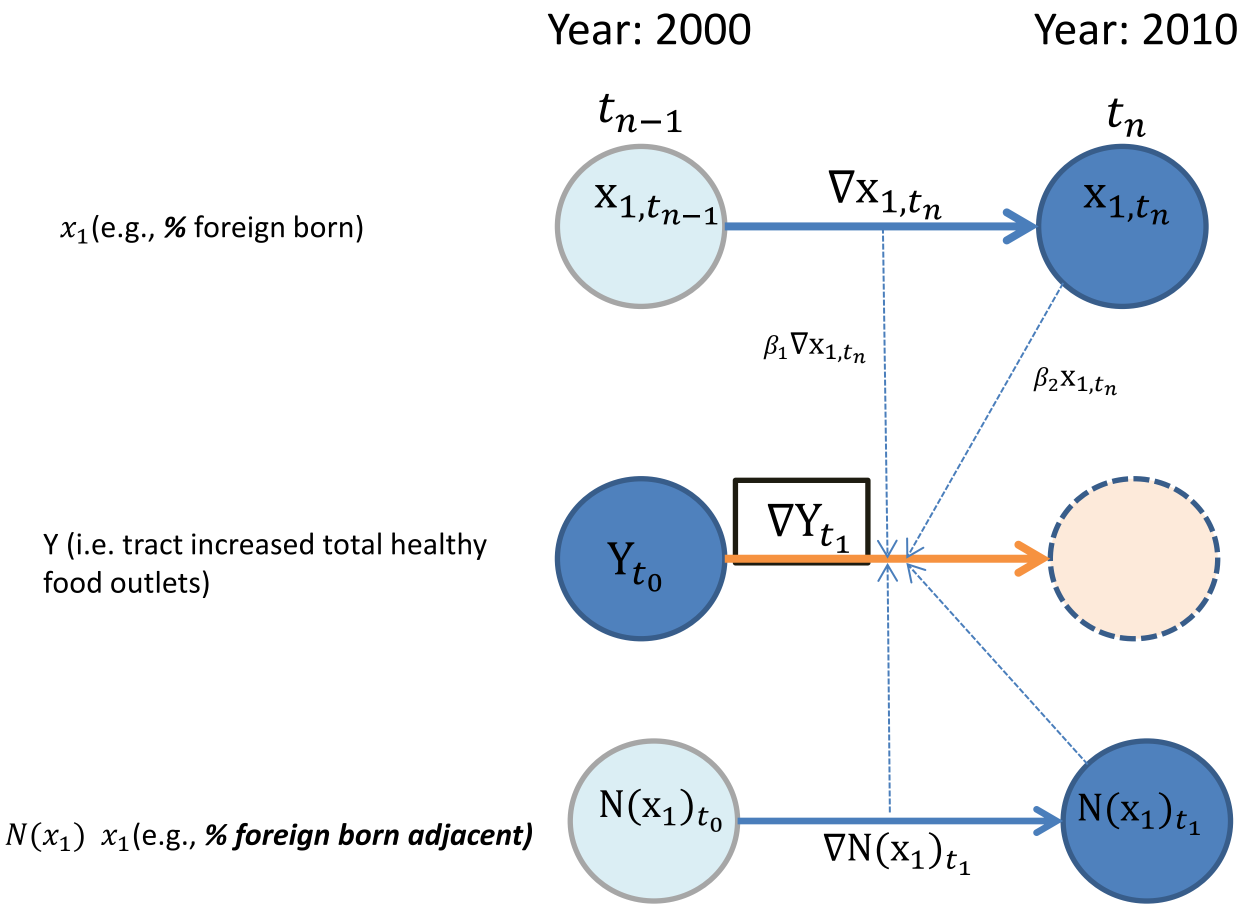
t_n

x_1 (e.g., % foreign born)

Y (i.e. tract increased total healthy food outlets)

$\mathrm{x}_{1,t_{n-1}}$
$\nabla \mathrm{x}_{1,t_n}$
x_{1,t_n}
$\beta_1 \nabla \mathrm{x}_{1,t_n}$
$\beta_2 \mathrm{x}_{1,t_n}$
Y_{t_0}
$\nabla \mathrm{Y}_{t_1}$

Conceptualizing the Model



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$\beta_2 \mathrm{x}_{1,t_n}$

Y (i.e. tract increased total healthy food outlets)

Y_{t_0}

$\nabla \mathrm{Y}_{t_1}$

$N(x_1)$ x_1(e.g., ***% foreign born adjacent)***

$\mathrm{N}(\mathrm{x}_1)_{t_0}$

$\nabla \mathrm{N}(\mathrm{x}_1)_{t_1}$

$\mathrm{N}(\mathrm{x}_1)_{t_1}$

Expansions & Considerations

Interactions in Explanatory Variables:

38 main effects
703 interactions
9056 observations.

Risks:

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Approaches:

Model Validation, **Resampling** and **Shrinkage/Regularization**

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Approaches:
Model Validation, **Resampling** and **Shrinkage/Regularization**

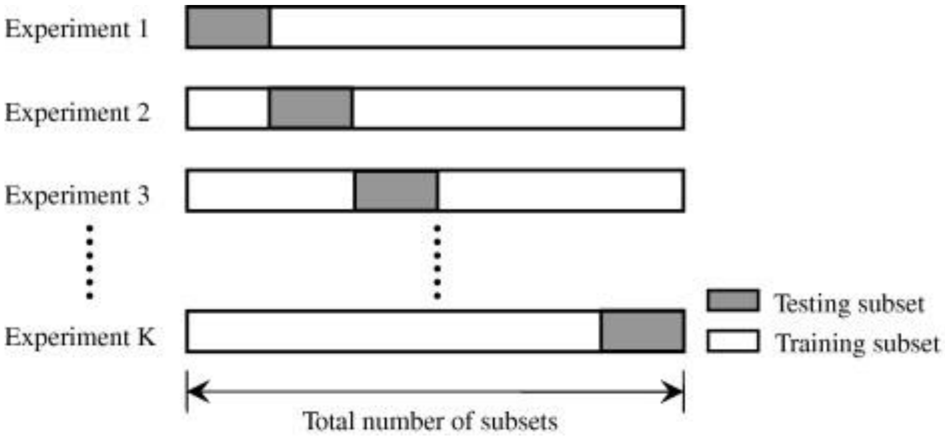
through **Cross-Validation, Bootstrapping, Lasso Shrinkage,** and **Model Averaging**

Generalization & Model Validation

Concerns regarding: **generalizability**, **interpretability**, and risk of **overfitting** relationships

K-fold cross-validation (CV)

- Divide into k subsets
- Exclude one subset as testing set; remaining k-1 subsets are combined to be the training set
- Fit model to training set, assess model on testing set



Generalization & Model Validation

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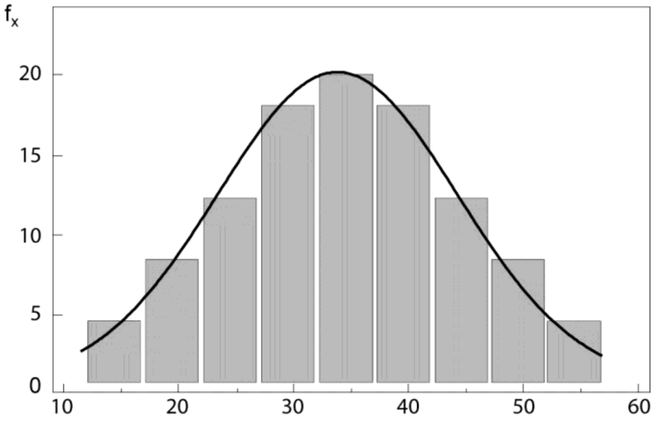
Non-parametric bootstrap

- Resample from empirical distribution with replacement.



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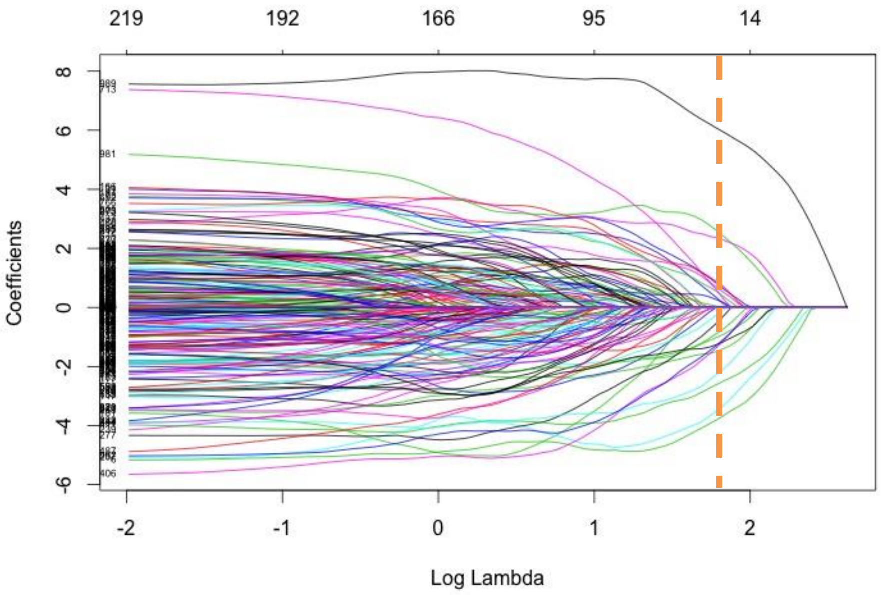
Regularization/Shrinkage

- Lasso penalization on Linear Regression
- $\hat{\beta}^{lasso} = argmin_{\beta}\left\{\frac{1}{2}\sum_{i=1}^{N}\left(y_i - \beta_0 - \sum_{j=1}^{p} x_{ij}\beta_j\right)^2 + \lambda\sum_{j=1}^{p}\left|\beta_j\right|\right\}$

Lasso Regularization Path



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Model Averaging:

- Bagging (Bootstrap Aggregation)

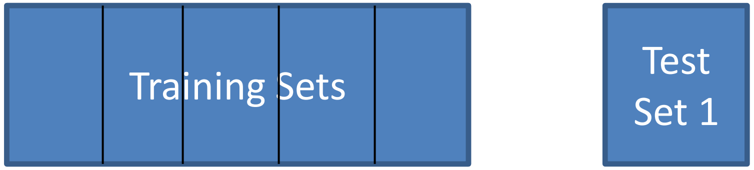
$$\hat{f}_{bag}(x) = \frac{1}{B} \sum_{b=1}^{B} \hat{f}^{*b}(x)$$

- Bayesian Model Averaging

$$\hat{\theta}_{\mathrm{BMA}} = \sum_{k=1}^{K} \hat{\theta}_k p\left(M_k \,|\, \mathbf{Z}\right)$$

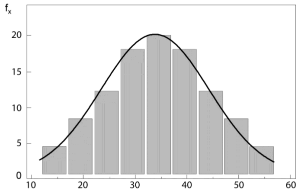
Generalization & Model Validation

1: Partition (k-fold CV)



Generalization & Model Validation

2: Resample



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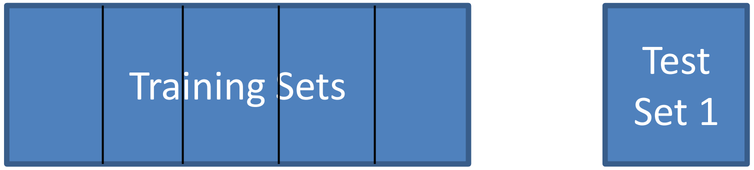
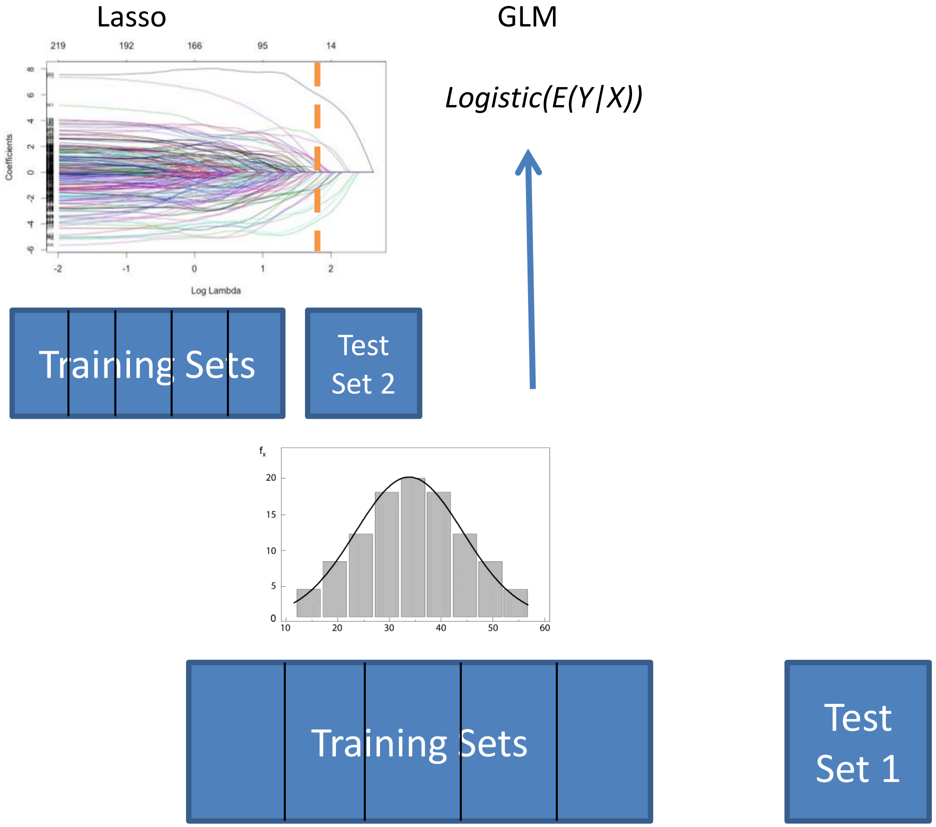


Training Sets

Test Set 1

Generalization & Model Validation



GLM

Logistic(E(Y|X))

Training Sets

Test Set 2

2: Resample

1: Partition (k-fold CV)

Training Sets

Test Set 1

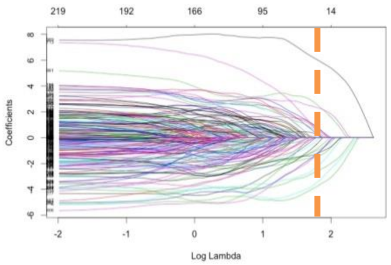
Generalization & Model Validation

4: Model averaging

$F_M(X): f(x_1),f(x_2),\ldots$

3: Fit and Evaluate Models

Lasso



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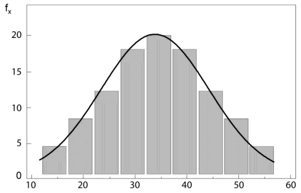


1: Partition (k-fold CV)

Training Sets

Test Set 1

Generalization & Model Validation

5: Evaluate prediction with resampled test set

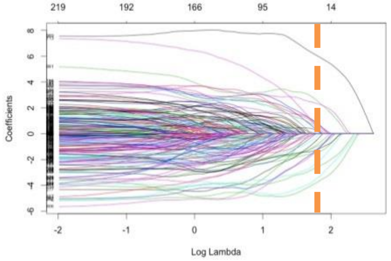
$Y = F_M(X)$ → $\{y,x\}$

4: Model averaging

$F_M(X)$: $f(x_1),f(x_2),\ldots$

3: Fit and Evaluate Models

Lasso



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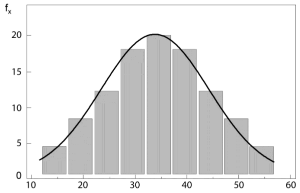
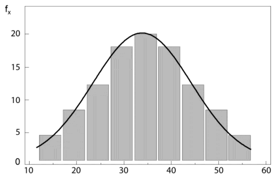
Logistic(E(Y|X))

Training Sets | Test Set 2

2: Resample





1: Partition (k-fold CV)

Training Sets | Test Set 1

Prediction

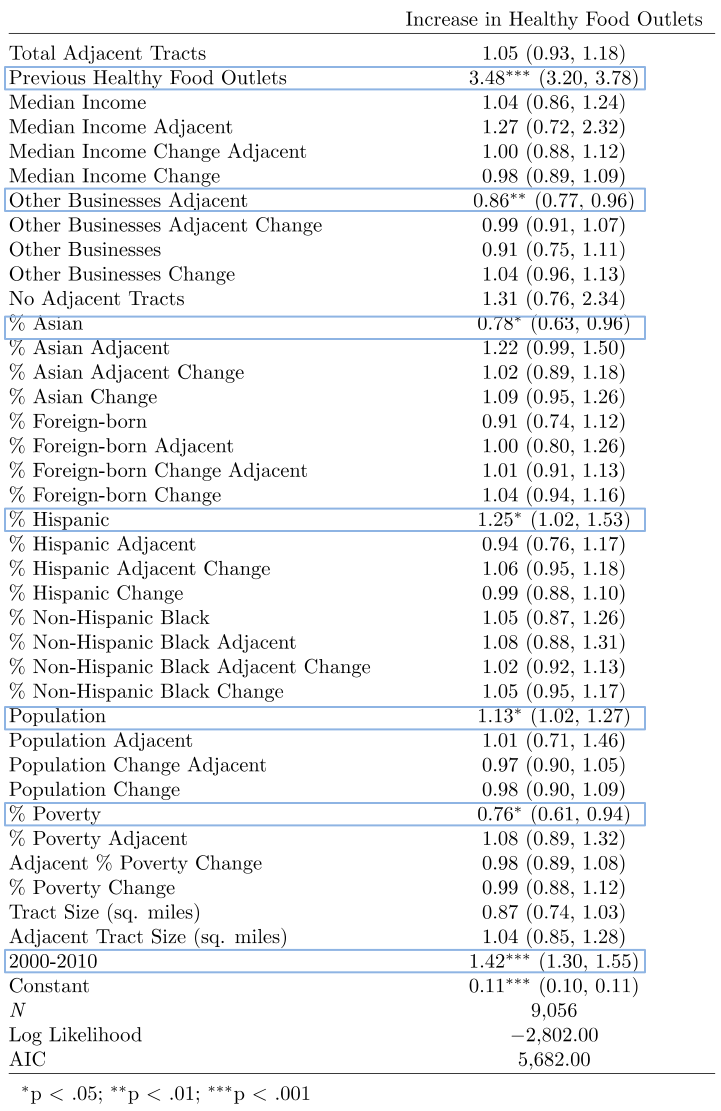
Results need correction

Misclassification

	GLM			Lasso (CV-min)			Lasso (1 Standard Error of CV-min)		
	Sample Fit	Bag	BMA	Sample Fit	Bag	BMA	Sample Fit	Bag	BMA
Training Set CV error	13.30%	13.29%	12.45%	13.25%	13.21%	12.39%	13.68%	13.63%	12.97%
Bootstrap Test Set Error	13.28%	13.66%	13.27%	13.28%	13.66%	13.23%	13.33%	13.40%	13.37%
Full Sample	13.22%	13.68%	13.21%	13.25%	13.68%	13.18%	13.30%	13.47%	13.29%

GLM Associations

Logistic Regression Results: OR(95% CI)

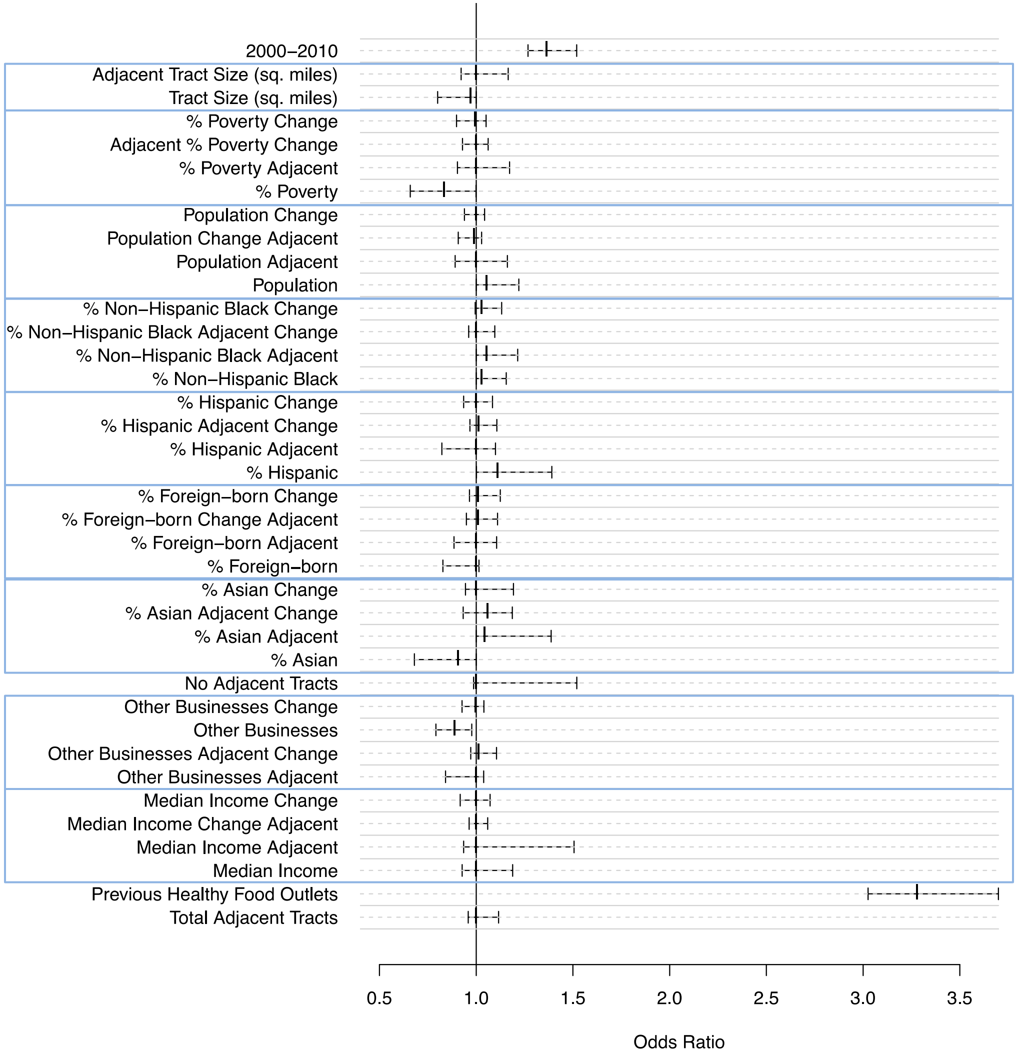


	Increase in Healthy Food Outlets
Total Adjacent Tracts	1.05 (0.93, 1.18)
Previous Healthy Food Outlets	3.48*** (3.20, 3.78)
Median Income	1.04 (0.86, 1.24)
Median Income Adjacent	1.27 (0.72, 2.32)
Median Income Change Adjacent	1.00 (0.88, 1.12)
Median Income Change	0.98 (0.89, 1.09)
Other Businesses Adjacent	0.86** (0.77, 0.96)
Other Businesses Adjacent Change	0.99 (0.91, 1.07)
Other Businesses	0.91 (0.75, 1.11)
Other Businesses Change	1.04 (0.96, 1.13)
No Adjacent Tracts	1.31 (0.76, 2.34)
% Asian	0.78* (0.63, 0.96)
% Asian Adjacent	1.22 (0.99, 1.50)
% Asian Adjacent Change	1.02 (0.89, 1.18)
% Asian Change	1.09 (0.95, 1.26)
% Foreign-born	0.91 (0.74, 1.12)
% Foreign-born Adjacent	1.00 (0.80, 1.26)
% Foreign-born Change Adjacent	1.01 (0.91, 1.13)
% Foreign-born Change	1.04 (0.94, 1.16)
% Hispanic	1.25* (1.02, 1.53)
% Hispanic Adjacent	0.94 (0.76, 1.17)
% Hispanic Adjacent Change	1.06 (0.95, 1.18)
% Hispanic Change	0.99 (0.88, 1.10)
% Non-Hispanic Black	1.05 (0.87, 1.26)
% Non-Hispanic Black Adjacent	1.08 (0.88, 1.31)
% Non-Hispanic Black Adjacent Change	1.02 (0.92, 1.13)
% Non-Hispanic Black Change	1.05 (0.95, 1.17)
Population	1.13* (1.02, 1.27)
Population Adjacent	1.01 (0.71, 1.46)
Population Change Adjacent	0.97 (0.90, 1.05)
Population Change	0.98 (0.90, 1.09)
% Poverty	0.76* (0.61, 0.94)
% Poverty Adjacent	1.08 (0.89, 1.32)
Adjacent % Poverty Change	0.98 (0.89, 1.08)
% Poverty Change	0.99 (0.88, 1.12)
Tract Size (sq. miles)	0.87 (0.74, 1.03)
Adjacent Tract Size (sq. miles)	1.04 (0.85, 1.28)
2000-2010	1.42*** (1.30, 1.55)
Constant	0.11*** (0.10, 0.11)
N	9,056
Log Likelihood	−2,802.00
AIC	5,682.00

*p < .05; **p < .01; ***p < .001

Add: Models with adjacent and time change as separate; correct results

Lasso Associations



same framework – correct the results

Conclusions

- Model validation is an important aspect of assessing generalizability.
- Selection of models fit to bootstrap samples using likelihood-based criteria and regularization may improve out-of-sample prediction.

Future Directions

- Time intervals
- Generalizability across localities
- Alternate Outcomes