Rebecca Scheidegger, Emily Padvorac, Dana Chermesh

FOOD DESERTS & BIRTH OUTCOMES

Machine Learning for Cities, NYU CUSP Spring 2018 | Prof. Daniel Neil

Motivation

Objective:

- Identifying the important factors impacting **low birth weight** and **preterm births** on the zip code level

Implications:

- Helping determine what **policy levers to pull** or what **demographic groups to focus** intervention programs on
- Department of Health

Low birth weight; Preterm Birth

Short-term impacts;

Long-term impacts:

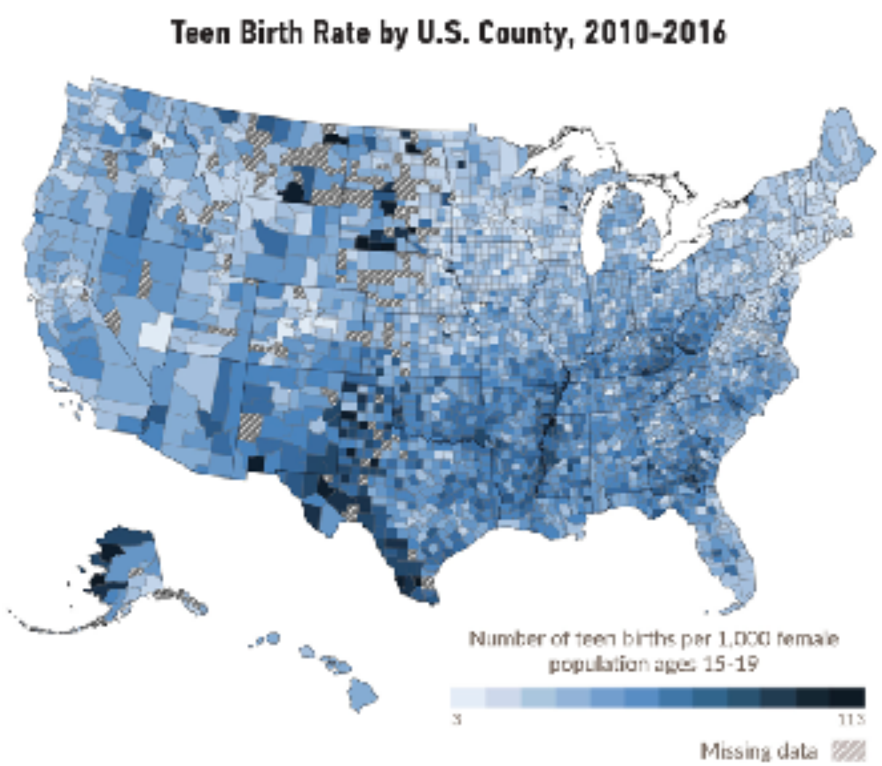
- neurological problems
- autism
- ADHD
- anxiety
- asthma
- hearing loss
- vision loss
- intestinal problems
- and more...

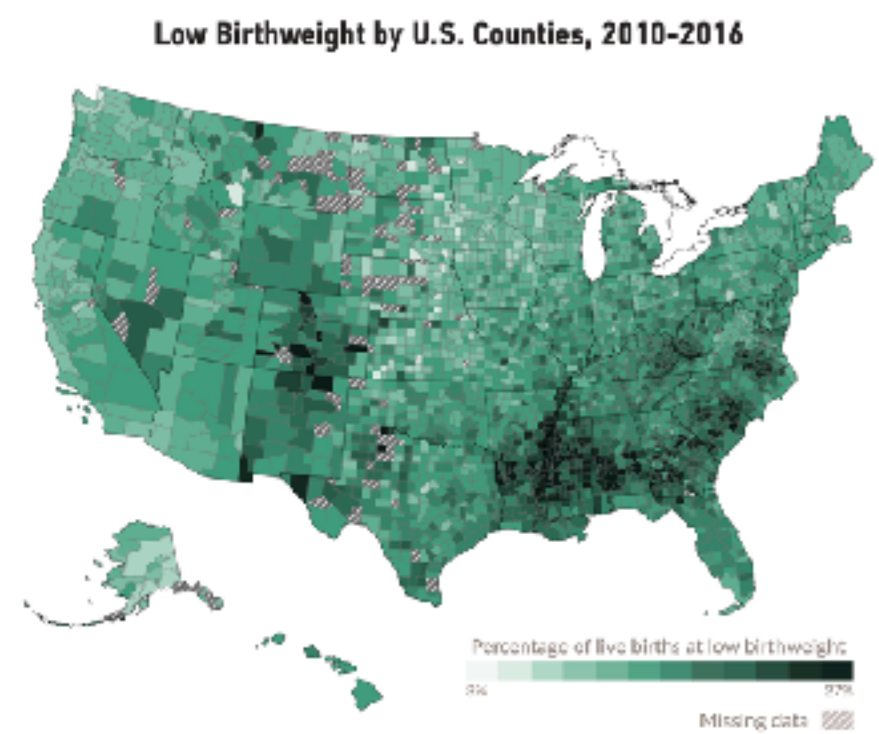
Low birth weight; Preterm Birth

Recent studies >>

*From: "**The Geography of Health in America**" // Alastair Boone, CityLab; published April 23th, 2018*
https://www.citylab.com/equity/2018/04/the-geography-of-health-in-america/557921/?utm_source=instagram

- County / State level





- Health Variables;

  > **Problematic to obtain** (data confidentiality) **&**

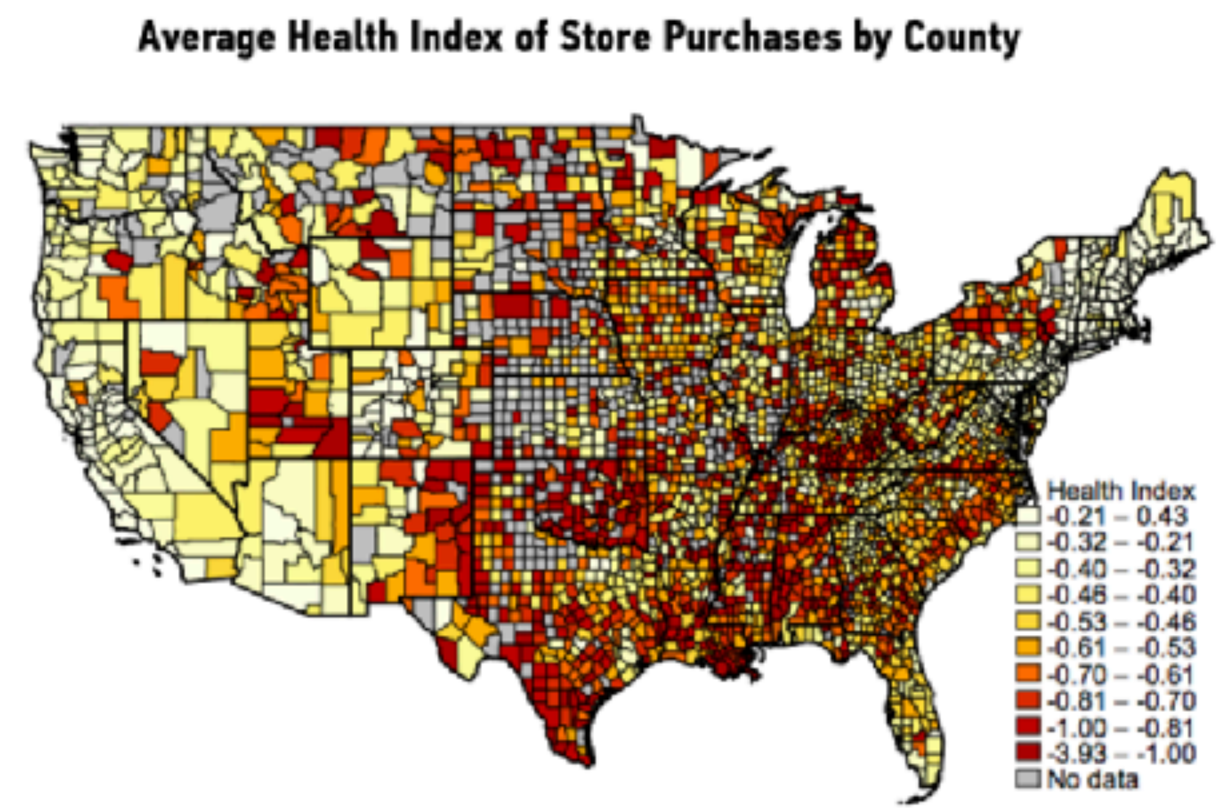
  > **Difficult to address** (educating the public)

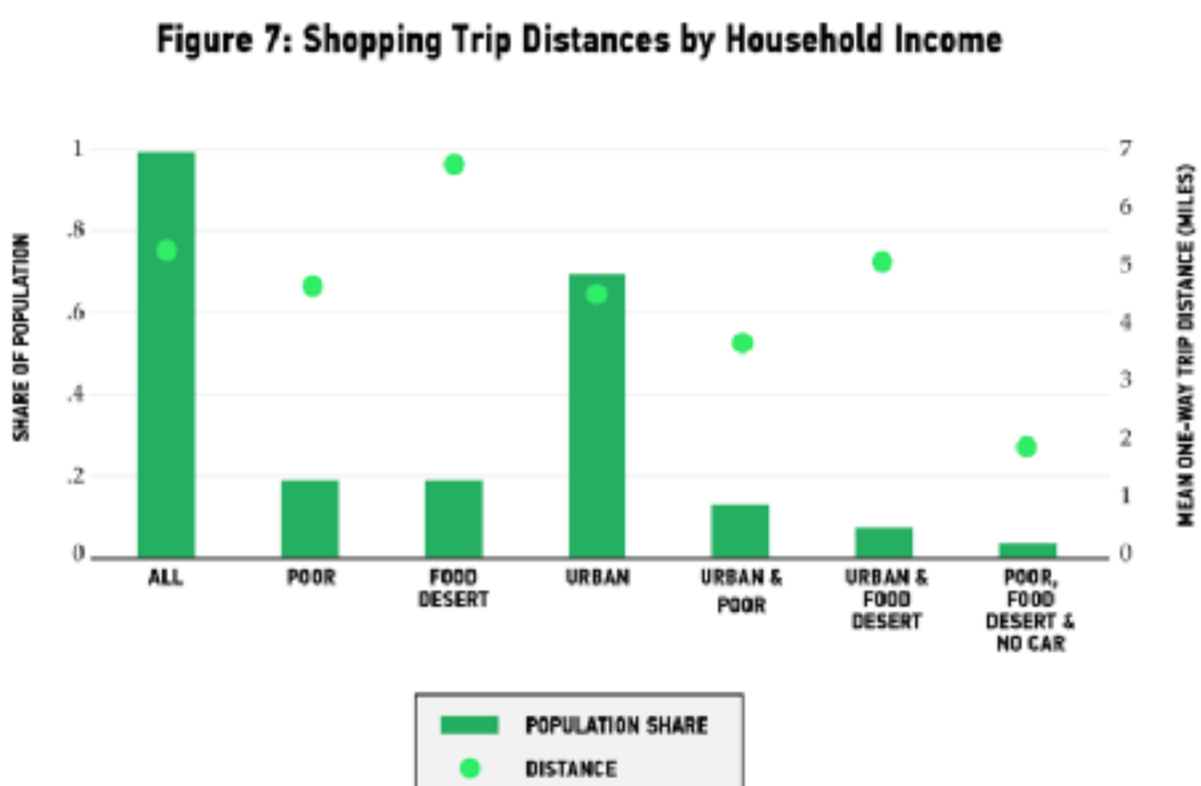
Food Deserts, Health, Inequality

Recent studies

Granularity of County >> Zip code

*From: "**It's not the food desert it's the inequality**" // Richard Florida, CityLab; published January 18, 2018*
https://www.citylab.com/equity/2018/01/its-not-the-food-deserts-its-the-inequality/550793/





Researchers found that access to higher-quality groceries doesn't change eating habits as much as might be expected. // Alex Brandon/AP

It's Not the Food Deserts: It's the Inequality

RICHARD FLORIDA JAN 18, 2018

A new study suggests that America's great nutritional divide goes deeper than the problem of food access within cities.

Data

ACS data

Variables of interest:

- %Foreign
- %Uninsured
- %Vehicle access
- %Foodstamps
- %Poverty
- Urban / Rural

Health data

Independent Variables:

- %Teen Birth

Dependent Variables:

- %Low Birth Weight
- %Premature Birth

---

data limitations! NYS only; data is not available country-wide

Data

ACS data

Variables of interest:

- %Foreign
- %Uninsured
- %Vehicle access
- %Foodstamps
- %Poverty
- Urban / Rural

Health data

Independent Variables:

- %Teen Birth

Dependent Variables:

- %Low Birth Weight
- %Premature Birth

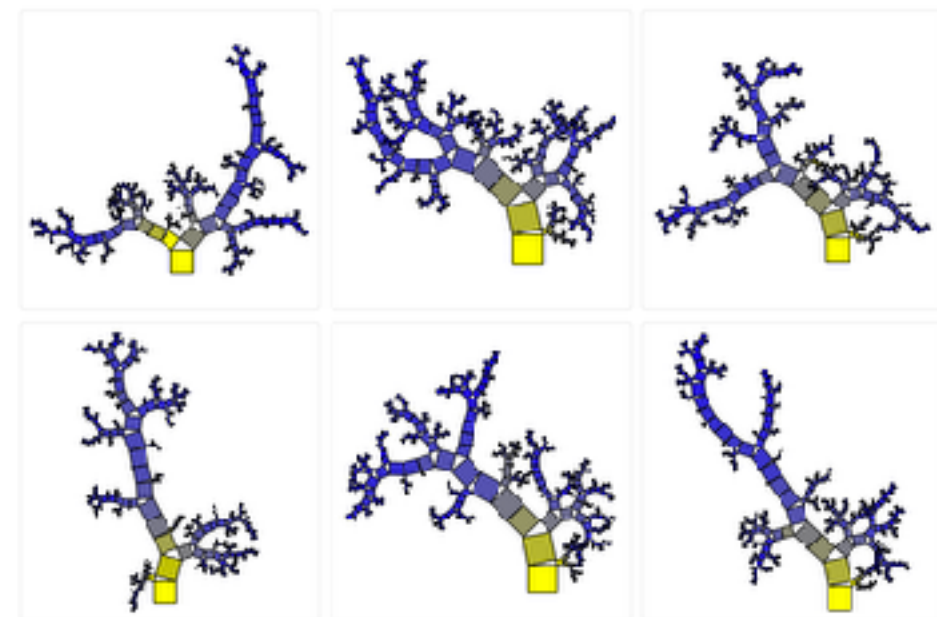
**** Not included:**

- Individual health data (BMI)
- Mother’s age groups
- Multiple birth factor

Methodology - Supervised Learning

Labeled data (ACS data + birth outcomes)

Two approaches >> in order to allowed results to be compared and contrasted to better understand the structure and accuracy of model choice

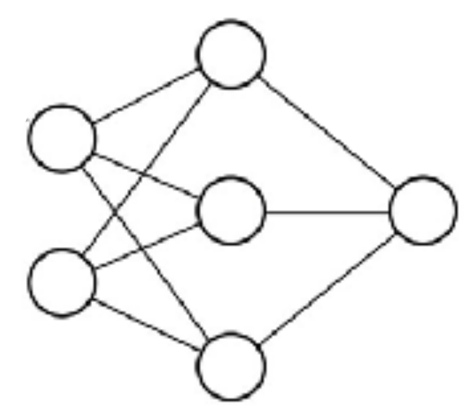


1 Random Forest;

- Feature importance
- Accuracy

2 Bayesian Networks

- Learn structure of relationships between Variables



Methodology - Supervised Learning

Labeled data (ACS data + birth outcomes)

Two approaches >> in order to allowed results to be compared and contrasted to better understand the structure and accuracy of model choice

1 Random Forest;

- Make **dummy variable** for the dependent variable based on **std**
- Test sample **30%**
- Parameter tuning for finding **best Max-depth**
- Compute **feature importance** according to Max-depth

Methodology - Supervised Learning

Labeled data (ACS data + birth outcomes)

Two approaches >> in order to allowed results to be compared and contrasted to better understand the structure and accuracy of model choice

2 Bayesian Networks

- Dummy variables for all variables in the network
- Best model and HillClimbSearch

```
In [9]: for i in dfunpre:
            dfunpre[i] = pd.qcut(dfunpre[i].rank(method='first'),4,labels=False)
        print(dfunpre.head())

         %Uninsured  %vehicle  %foodStamp  %poverty  %Foreign  urban  \
zipcode
10001             1         3           3         3         3      1
10002             2         3           3         3         3      1
10003             1         3           3         1         3      1
10004             1         3           3         0         3      1
10005             1         3           3         2         3      1

         %PrematureBirth
zipcode
10001                  2
10002                  1
10003                  1
10004                  1
10005                  2
```

Results

1 Random Forest

Low Birth Weight

Premature Birth

```
Best parameter value: {'max_depth': 8}
Accuracy =  0.629268292683
```

	variables	importance
1	%Uninsured	0.255918
3	%foodStamp	0.246174
4	%poverty	0.236059
6	%TeenBirthRate	0.105216
0	%Foreign	0.076929
2	%vehicle	0.0706497
5	urban	0.00905481

Results

1 Random Forest

Low Birth Weight

```
Best parameter value: {'max_depth': 8}
Accuracy =  0.629268292683
```

Premature Birth

```
Best parameter value: {'max_depth': 9}
Accuracy =  0.604118993135
```

	variables	importance
1	%Uninsured	0.240602
3	%foodStamp	0.239732
4	%poverty	0.237192
6	%TeenBirthRate	0.114532
2	%vehicle	0.0733406
0	%Foreign	0.058583
5	urban	0.0360183

Results

1 Random Forest

Low Birth Weight

Feature Importance:

1. % Uninsured; **25.6%**
2. % Food stamps; **24.6%**
3. % Poverty; **23.6%**
4. % Teen Birth Rate 10%
5. % Foreign + Vehicle Access
6. Urban / rural

Premature Birth

Feature Importance:

1. % Uninsured; **24%**
2. % Food stamps; **24%**
3. % Poverty; **23.7%**
4. % Teen Birth Rate 11%
5. % Foreign
6. Urban / rural

for RF; accuracy ~ 60-63%:

Both negative birth outcomes showed relatively similar results

Results

2 Bayes Nets

Low Birth Weight

Premature Birth

```
hc = HillClimbSearch(train, scoring_method=BicScore(train))
best_model = hc.estimate()
print(best_model.edges())
```

```
[('urban', '%foodStamp'), ('%Foreign', 'urban'), ('%TeenBirthRate', '%poverty'), ('%poverty', '%Uninsured'), ('%pover
ty', '%vehicle'), ('%vehicle', '%LowBirthWeight'), ('%vehicle', '%Foreign')]
```

```
best_model.fit(train, estimator=BayesianEstimator, prior_type='K2')
for cpd in best_model.get_cpds():
    print("CPD of {variable}:".format(variable=cpd.variable))
    print(cpd)
```

```
CPD of urban:
 ------------------------------------------------------------------------------------------------------------
| %Uninsured(2) | 0.1384083044982699  | 0.25806451612903225 | 0.3192982456140351  | 0.32989690721649484 |
+---------------+---------------------+---------------------+---------------------+---------------------+
| %Uninsured(3) | 0.08650519031141868 | 0.14695340501792115 | 0.312280701754386   | 0.40893470790378006 |
+---------------+---------------------+---------------------+---------------------+---------------------+
CPD of %vehicle:
+-------------+---------------------+---------------------+---------------------+---------------------+
| %poverty    | %poverty(0)         | %poverty(1)         | %poverty(2)         | %poverty(3)         |
+-------------+---------------------+---------------------+---------------------+---------------------+
| %vehicle(0) | 0.44982698961937717 | 0.25089605734767023 | 0.20701754385964913 | 0.09621993127147767 |
+-------------+---------------------+---------------------+---------------------+---------------------+
| %vehicle(1) | 0.29411764705882354 | 0.3727598566308244  | 0.23508771929824562 | 0.10309278350515463 |
+-------------+---------------------+---------------------+---------------------+---------------------+
| %vehicle(2) | 0.2041522491349481  | 0.24372759856630824 | 0.34035087719298246 | 0.26804123711340205 |
+-------------+---------------------+---------------------+---------------------+---------------------+
| %vehicle(3) | 0.05190311418685121 | 0.13261648745519714 | 0.21754385964912282 | 0.5326460481099656  |
+-------------+---------------------+---------------------+---------------------+---------------------+
```

```
predicted_test = best_model.predict(test.loc[:,"%Uninsured":"urban"])
print "Out of sample:",(test.loc[:,'%LowBirthWeight']==predicted_test['%LowBirthWeight']).mean()
```

```
Out of sample: 0.3071808510638298
```

Results

2 Bayes Nets

Low Birth Weight

Premature Birth

```
hc = HillClimbSearch(train, scoring_method=BicScore(train))
best_model = hc.estimate()
print(best_model.edges())
```

```
[('urban', '%foodStamp'), ('%Foreign', 'urban'), ('%TeenBirthRate', '%poverty'), ('%poverty', '%Uninsured'), ('%pover
ty', '%vehicle'), ('%vehicle', '%PrematureBirth'), ('%vehicle', '%Foreign')]
```

```
best_model.fit(train, estimator=BayesianEstimator, prior_type='K2')
for cpd in best_model.get_cpds():
    print("CPD of {variable}:".format(variable=cpd.variable))
    print(cpd)
```

```
| %TeenBirthRate(1) | 0.24735    |
+-------------------+------------+
| %TeenBirthRate(2) | 0.241166   |
+-------------------+------------+
| %TeenBirthRate(3) | 0.25       |
+-------------------+------------+
CPD of %foodStamp:
+---------------+---------------------+---------------------+---------------------+---------------------+
| urban         | urban(0)            | urban(1)            | urban(2)            | urban(3)            |
+---------------+---------------------+---------------------+---------------------+---------------------+
| %foodStamp(0) | 0.22758620689655173 | 0.10469314079422383 | 0.48986486486486486 | 0.17793594306049823 |
+---------------+---------------------+---------------------+---------------------+---------------------+
| %foodStamp(1) | 0.30689655172413793 | 0.23826714801444043 | 0.2635135135135135  | 0.1494661921708185  |
+---------------+---------------------+---------------------+---------------------+---------------------+
| %foodStamp(2) | 0.2655172413793103  | 0.37184115523465705 | 0.10472972972972973 | 0.3487544483985765  |
+---------------+---------------------+---------------------+---------------------+---------------------+
| %foodStamp(3) | 0.2                 | 0.2851985559566787  | 0.14189189189189189 | 0.3238434163701068  |
+---------------+---------------------+---------------------+---------------------+---------------------+
```

```
predicted_test = best_model.predict(test.loc[:,"%Uninsured":"urban"])
print "Out of sample:",(test.loc[:,"%PrematureBirth"]==predicted_test["%PrematureBirth"]).mean()
```

```
Out of sample: 0.2925531914893617
```

Results

2 Bayes Nets

Low Birth Weight

Premature Birth

```
[('urban', '%foodStamp'), ('%Foreign', 'urban'), ('%TeenBirthRate', '%poverty'), ('%poverty', '%Uninsured'), ('%pover
ty', '%vehicle'), ('%vehicle', '%PrematureBirth'), ('%vehicle', '%Foreign')]
```

for BN; accuracy ~ 30%:

Identical structure was learned for both negative birth outcomes

Results

Comparison **RF** vs **BN**

Higher Accuracy (60-63%)

Accuracy (30%)

+ We want more data!

Thank You :)