### Health Outcomes v. Warehouse Location

Something.

### Intro: Diesel Trucks are Bad For Babies



FEATURES DROPPED

SURPRISING FEATURES

BLURB

### THE PROBLEM STATEMENT SLIDE



- What is the (quantifiable) effect of increased warehouse presence in California in the last decade on emergency healthcare?
- How well do the CalEnviroScreen scores reflect emergency healthcare counts?
- What indicators from the CalEnviroScreen dataset best determine the number of emergency healthcare visits?

### Aggregated Modeling With Additional Features



As Data Scientists in OEHHA, we are tasked with developing models aggregating the four time-points from each report with additional information on warehouse density to assess primary mitigating factors addressing negative health outcomes.

# Data Source: California EnviroScreen reports



#### From the California Office of Environmental Health Hazard Assessment

#### https://oehha.ca.gov/calenviroscreen

A series of four datasets and reports, published 20–, 20–, 20–, and 20–, with pollution, basic health, and socioeconomic measurements for each of California's zip codes or census tracts.

These measurements are compiled into a small number of summary scores, including a broad California EnviroScreen score indicating the regions with the most pressing needs.

#### The CalEnviroScreen Model

EnviroScreen-specific "scores" are derived from measurements.

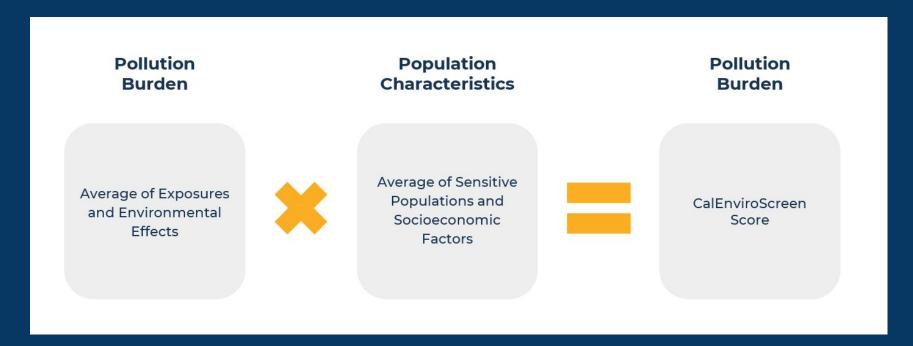
- Pollution Burden Score
  - Exposures
    - Ozone concentrations
    - Particulate matter emissions and concentrations (diesel, PM2.5)
    - Drinking water contaminants, lead risk
    - Toxic releases from facilities, pesticide use
    - Traffic density
  - Environmental Effects
    - Solid waste, sites
    - Groundwater threats and impaired water body count

#### The CalEnviroScreen Model

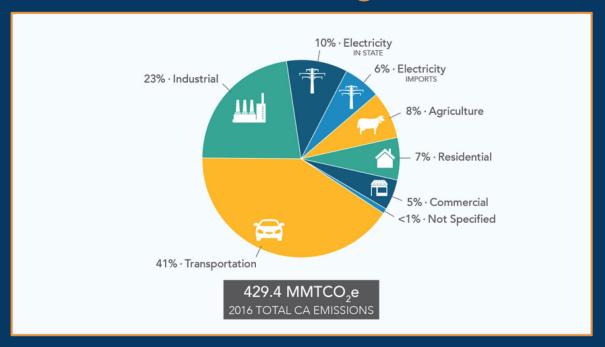
EnviroScreen-specific "scores" are derived from measurements, also included in the dataset. Impact weights are determined by the CalEPA.

- Population characteristics
  - Sensitive population
    - Asthma
    - Cardiovascular disease
    - Low birth weight infants
  - Socioeconomic factors
    - Educational attainment
    - Housing burdened low income households
    - Linguistic isolation
    - Poverty
    - Unemployment

#### The CalEnviroScreen Model



### Motivation: Assessing Effect of Emission Sources



**SOURCE:** CA Air Resources Board, 2018 GHG Emission Inventory, July 2018 https://www.arb.ca.gov/cc/inventory/data/data.htm

## Motivation: Emissions Exceptions

#### Your vehicle does not need a smog inspection if your:

- Gasoline-powered vehicle is a 1975 year model or older (This includes motorcycles and trailers.)
- Diesel-powered vehicle is a 1997 and older year model OR with a Gross Vehicle Weight of more than 14,000 pounds.
- Powered by natural gas and weighs more than 14,000 pounds.
- · An electric vehicle.
- Gasoline-powered and less than eight model-years old.

SOURCE: CA DMV dmv.ca.gov/portal/vehicle-registration/smog-inspections/



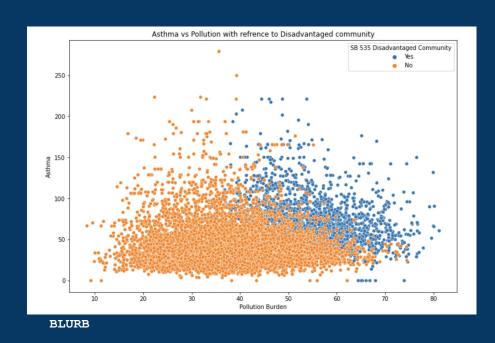
1995 Freightliner for Sale in San Rafael, Marin County, San Francisco Bay Area, CA

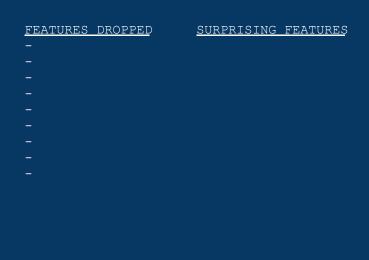
### Motivation: Landscape Changes



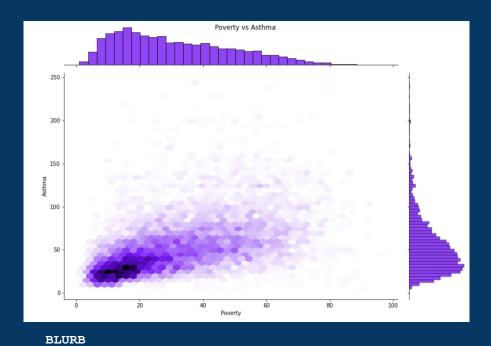
SOURCE: riversidewarehouses.com/listings/1020-prosperity-way-beaumont-ca-92223

### EDA with with health, pollution, and Poverty(SB)





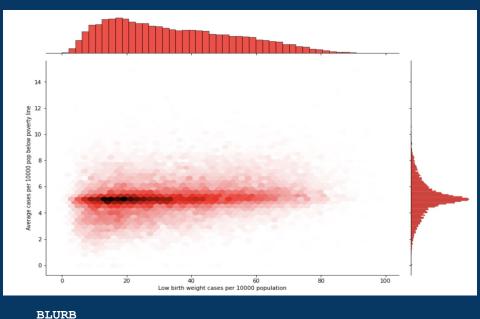
### EDA visuals cont. (marshall)



FEATURES DROPPED

SURPRISING FEATURES

### Most important features for health cont.



FEATURES DROPPED

SURPRISING FEATURES

### EDA: Census data info – warehouse counts



Broad statistics on warehouse counts

MANIPULATION

SURPRISING FEATURES

Joined onto
CAES data by tract
or zip

Changes with time

Joined onto
CAES data by tract
or zip

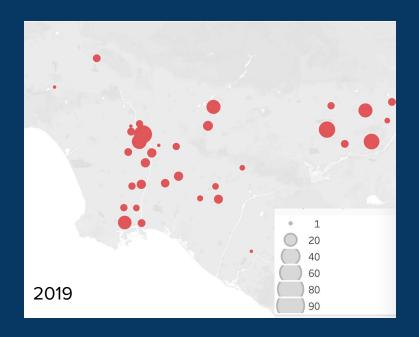
Time by zip — board warehouse business changes.

Or, just time with california as a whole.

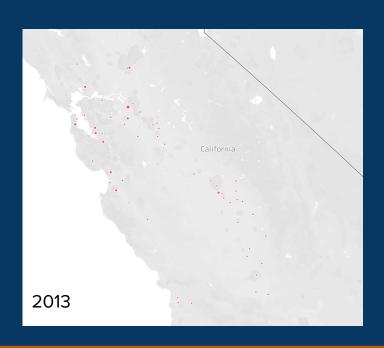


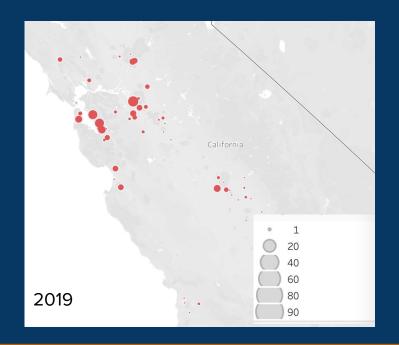
### Time by zip — board warehouse business changes.

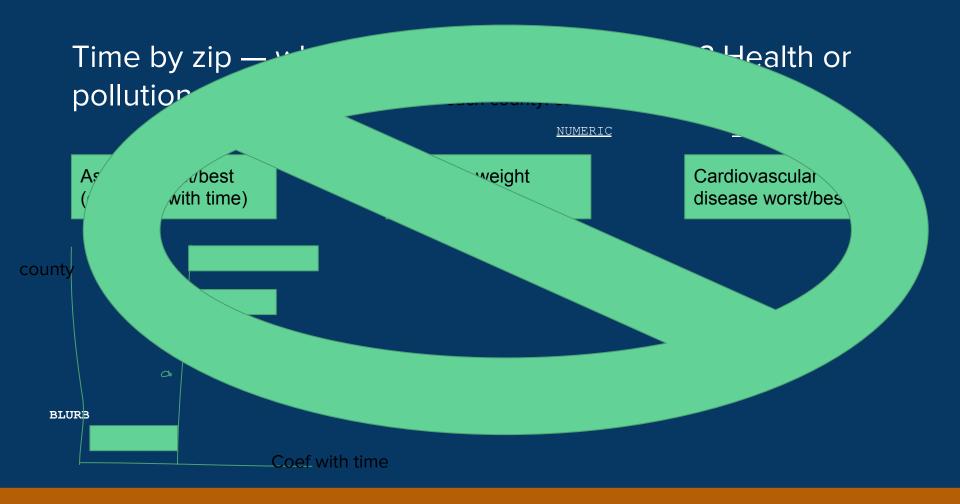




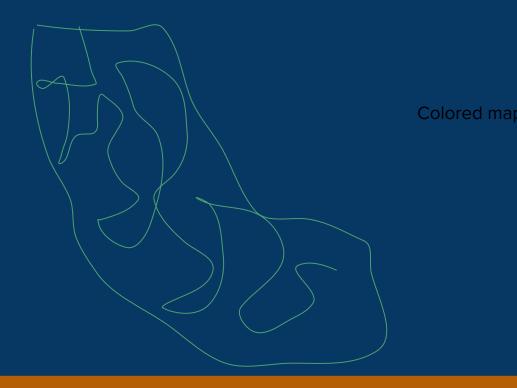
### Time by zip — board warehouse business changes.



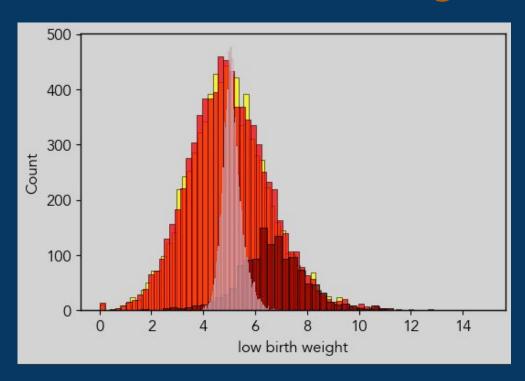




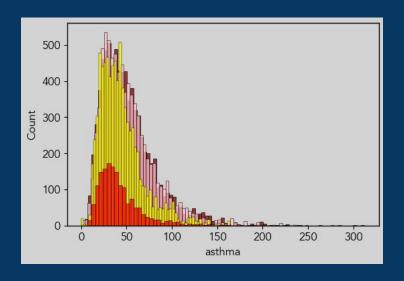
# Time by zip — what are the biggest changers? Health or pollution Only fitting four values for each county: caes 1, 2, 3, 4 years.

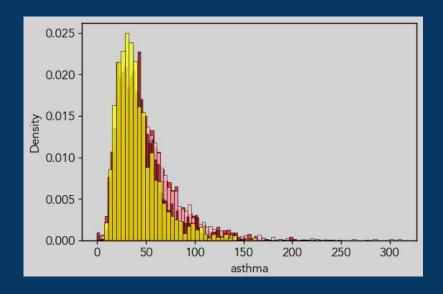


## EDA: Low-Birth Weight

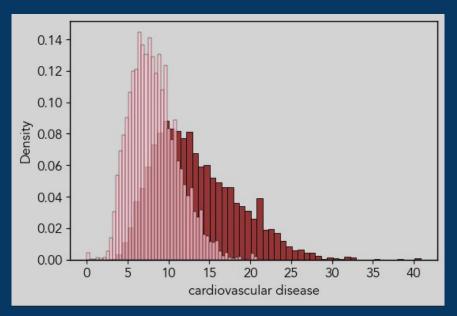


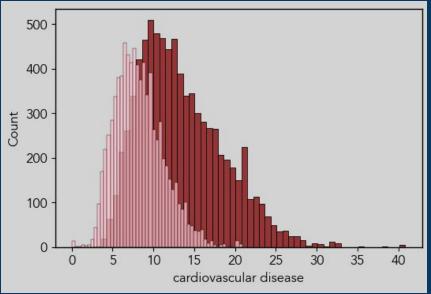
### EDA: Asthma



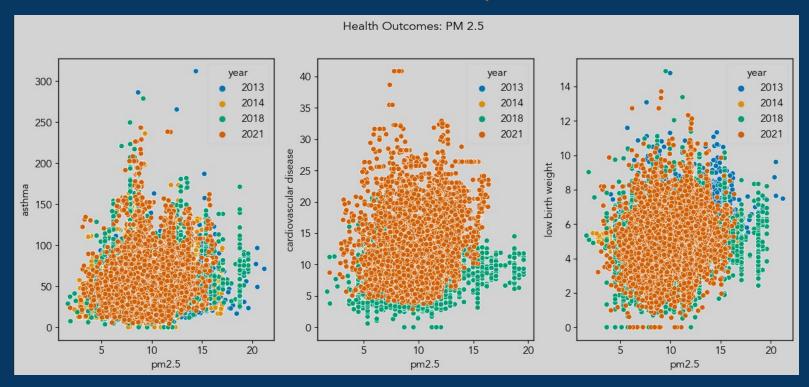


### **EDA:** Cardiovascular

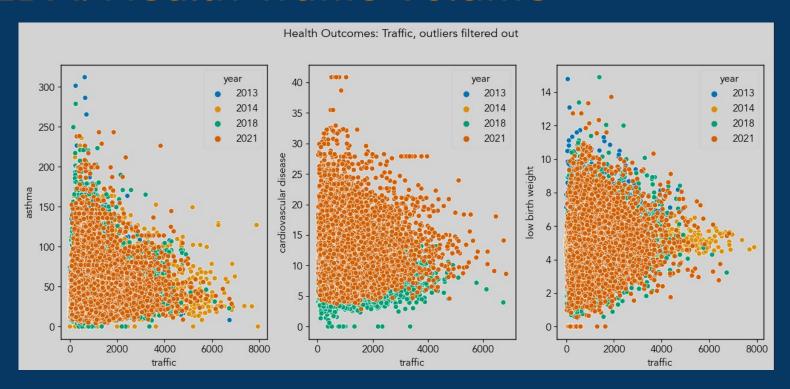




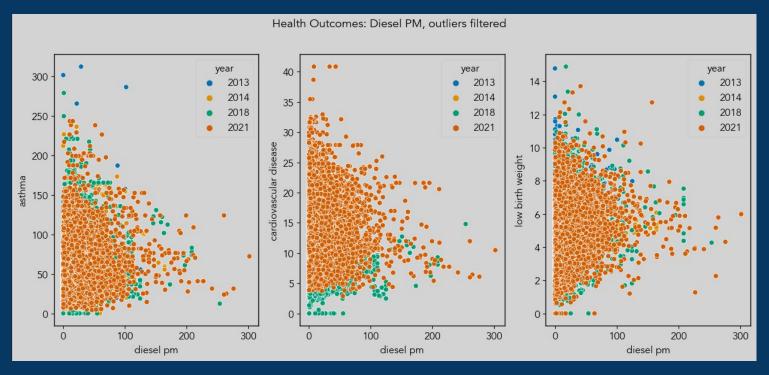
## EDA: Health Outcomes, PM 2.5



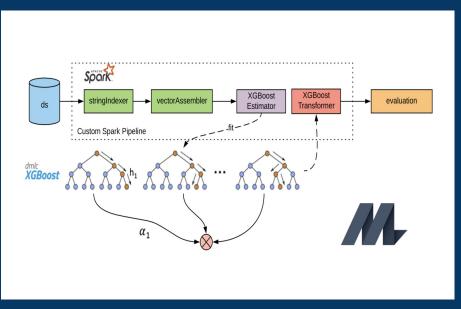
### **EDA:** Health Traffic Volume



## EDA: Health Outcomes, Diesel PM



#### XGboost, scaled, highest correlated features for Asthma



FEATURES

<u>Interpretation</u>

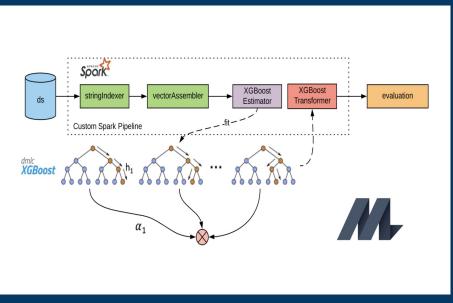
#### BLURE

 XGBoost can be used directly for regression predictive modeling.

#### **FINAL METRICS**

Train Accuracy: 0.9472151826696329 Test Accuracy: 0.7639090300436409 RMSF score: 14.376141

#### XGboost GS CV fit to best params Asthma



Interpretation

BLURB

**FINAL METRICS** 

Train Accuracy: 0.9472151826696329 Test Accuracy:0.7639090300436409 RMSE score:14.376141

## Model 2(marshall) Random Forest Reg



NUMERIC

CATEGORICAL

BLURB FINAL METRICS

#### Linear model: time and space only



NUMERIC

CATEGORICAL

Year
Latitude
longitude

BLURB

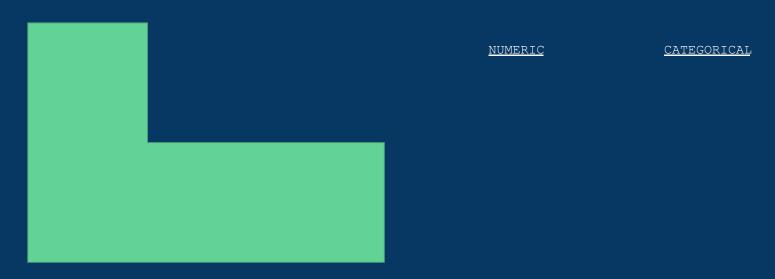
FINAL METRICS

Asthma - (0.042, 0.060)

Low birth weight - (0.007, 0.010)

Cardiovascular disease - (0.38, 0.38)

### Linear model: CAES score features only



BLURB FINAL METRICS

Do this to evaluate the CAES scores. "Have they done the feature engineering for us already?"

# Linear model: "Selected columns" (pollution and industry info. Most of the features.)



NUMERIC

CATEGORICAL

BLURB
No year. No space. No CAES specific scores.

r^2
Asthma - 0.593
Low birth weight - 0.385
Cardiovascular disease - 0.497

#### More on linear "selected features."

NUMERIC

CATEGORICAI

Which features were most influential on the linear scale? (not svd/PCR, but just relative to scaled data. This is coefficient relative to scaled data.)

BLURE

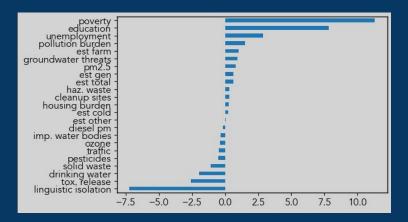
No year. No space. No CAES specific scores.

**FINAL METRICS, R^2:** 

Asthma - 0.593 Low birth weight - 0.385 Cardiovascular disease - 0.497

### Model: SVR

Epsilon-Support Vector Regression regularization: L2, C = 1



Feature Importances: really highlights

UMERIC CATEGORIO

FINAL METRICS

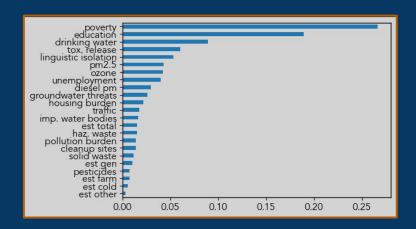
## Model: Random Forest Regression

```
n-estimators = 100
max depth = 10
```

```
max_leaf_nodes = 10
max_features : auto
```

NUMERIC

CATEGORICAL



different importances:

FINAL METRICS

Labrador keep this slide

Bulldog

n Shepherd

Yorkshire Terrier

Boxer

Australian Shepherd

Dachshund

Rottweiler



French Bulldog

Great Dane



ish Cocker



American Staffordshire Terrier



Chihuahua

berian Husky



Shih Tzu



Doberman Pinscher