Neural Network Models for Neighborhood Effects Research

Tolga Tasdizen

Scientific Computing and Imaging Institute

University of Utah

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Outline

- Part I: Built environment features
  1. Construct built environment features using computer vision models and publicly available Google Street View images
  2. Examine relationships between these features and demographic characteristics of residents, health outcomes.
- Part II: Alternative forms of supervision
  - Direct regression model
  - Hybrid model

What is Google Street View?

- Official launch in the United States in 2007
- Google Street View (GSV, a component of Google Maps): a source of 'big data' characterized by
  - high spatial resolution
  - panoramic views of homes, streets, businesses and neighborhoods at eye-level

PILOT: Using GSV to assess the built environment characteristics of 3 cities

- December 2016-February 2017, we obtained
  - 227,000 images for Chicago
  - 150,000 for Salt Lake City
  - 53,000 for Charleston
- Images were collected from all road intersections and a random sample of street segments approximately 50 meters apart

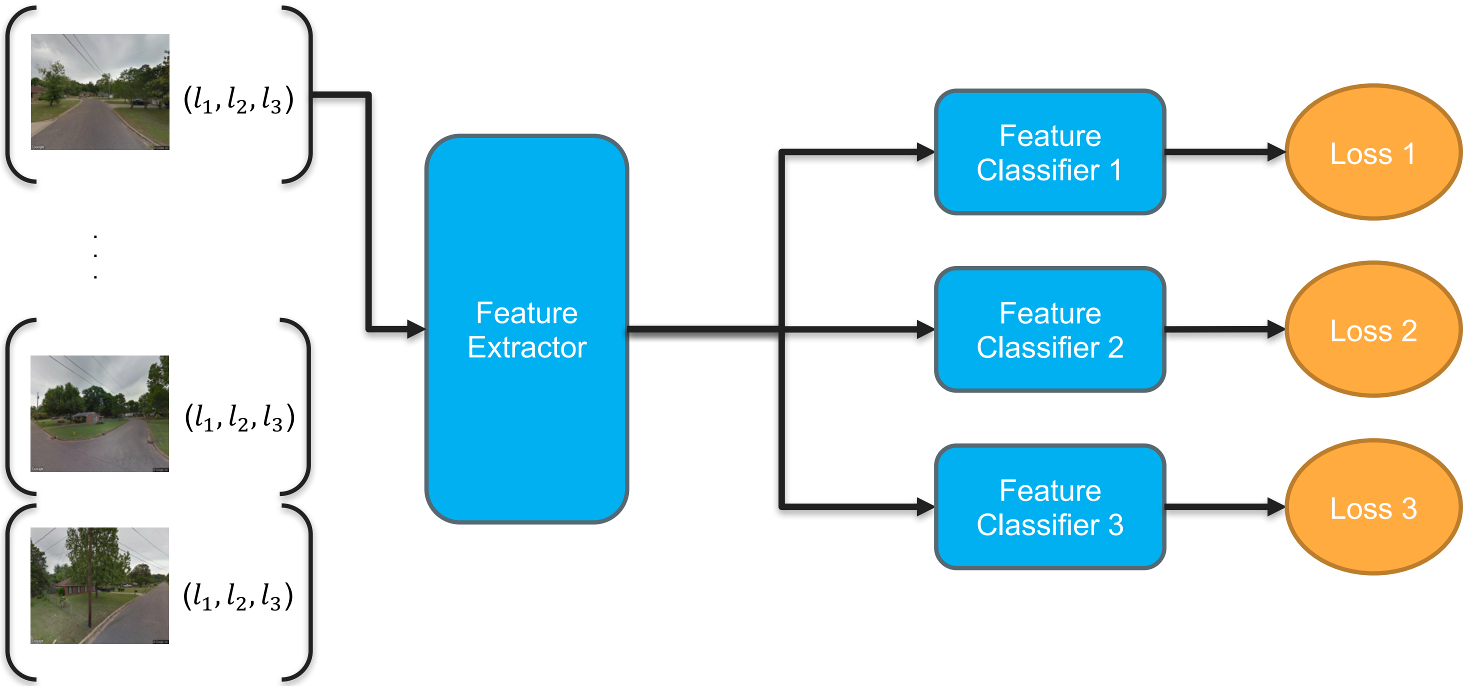
Built environment features

- Each image had three binary labels for the following built environment features

1. presence of a crosswalk (yes/no)
2. building type (single-family detached house vs. other)
3. street greenness/landscaping (street trees and street landscaping comprised at least 30% of the image (yes/no).

Computer vision

- Deep convolutional network
  Visual Geometry Group
  (VGG-19 model)
  - Commonly used in transfer learning
  - 3 built environment features
  - 16,000 images labeled
  - 80%/20% train/test split
- Testing accuracies
  - 84.6% not single family home
  - 85.4% green 30
  - 93.0% crosswalk




green 30 – prediction: 1 true label: 1
crosswalks – prediction: 1 true label: 1
not SFH – prediction: 1 true label: 1
Google
© 2016 Google


green 30 – prediction: 1 true label: 1
crosswalks – prediction: 0 true label: 0
not SFH – prediction: 0 true label: 0
Google
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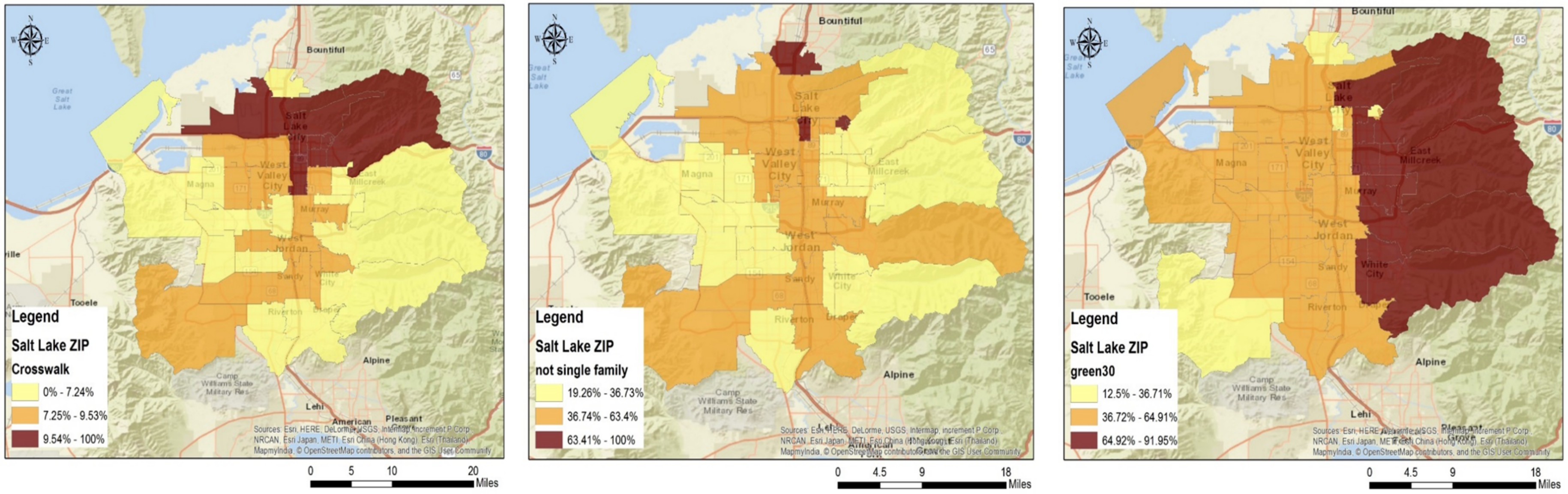
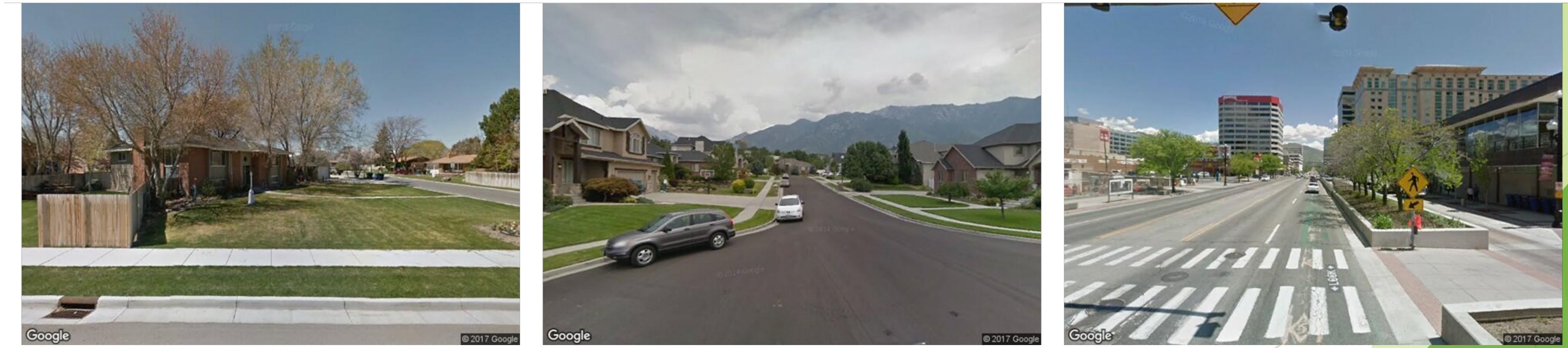
Zip code distribution of built environment characteristics in Salt Lake City





Nguyen et al, Neighbourhood looking glass: 360º automated characterisation of the built environment for neighbourhood effects research, J Epidemiol Community Health, 2018

Table 2. Built environment predictors of adult obesity and diabetes[a], Salt Lake City

	Obese	Diabetes
Built environment characteristics	Prevalence Ratio (95% CI)[b]	Prevalence Ratio (95% CI)[b]
Green streets		
3rd tertile (highest)	0.73 (0.63, 0.85)	0.86 (0.77, 0.96)
2nd tertile	0.99 (0.92, 1.06)	1.03 (0.97, 1.08)
Crosswalks		
3rd tertile (highest)	0.76 (0.69, 0.85)	0.87 (0.80, 0.95)
2nd tertile	1.02 (0.97, 1.07)	1.01 (0.95, 1.06)
Commercial buildings/apartments		
3rd tertile (highest)	0.79 (0.67, 0.94)	0.81 (0.67, 0.98)
2nd tertile	0.93 (0.86, 1.01)	0.91 (0.84, 0.99)
N	727,737	736,218

[a]Data source for health outcomes: Utah Population Database.

[b]Adjusted Poisson models were run for each outcome separately. Models controlled for individual level age, sex, race, ethnicity, education, and marital status as well as zip code level population density, percent of the population 65 years and older, percent Hispanic, percent black, median household income, and percent householder living in current residence for five years or more. Built environment characteristics were categorized into tertiles, with the lowest tertile serving as the referent group. Standard errors were adjusted for clustering of values at the zip code level.

Part II: USA wide data collection

- Used road network files from 2017 Census Topologically Integrated Geographic Encoding and Referencing data set.
  - Identified coordinates of street intersections
- Used Google's Street View Image Application Programming Interface (API) to obtain images.
- In total, we collected 31 million images from across the United States
  - Four images per pair of geocoordinates
- Additional built environment features: single lane, visible wires

Predictions
Green30: 0 CrossWalk: 0
Not SFH: 1 Single Lane: 0
3 or more Lane: 0
Visible Wires: 1

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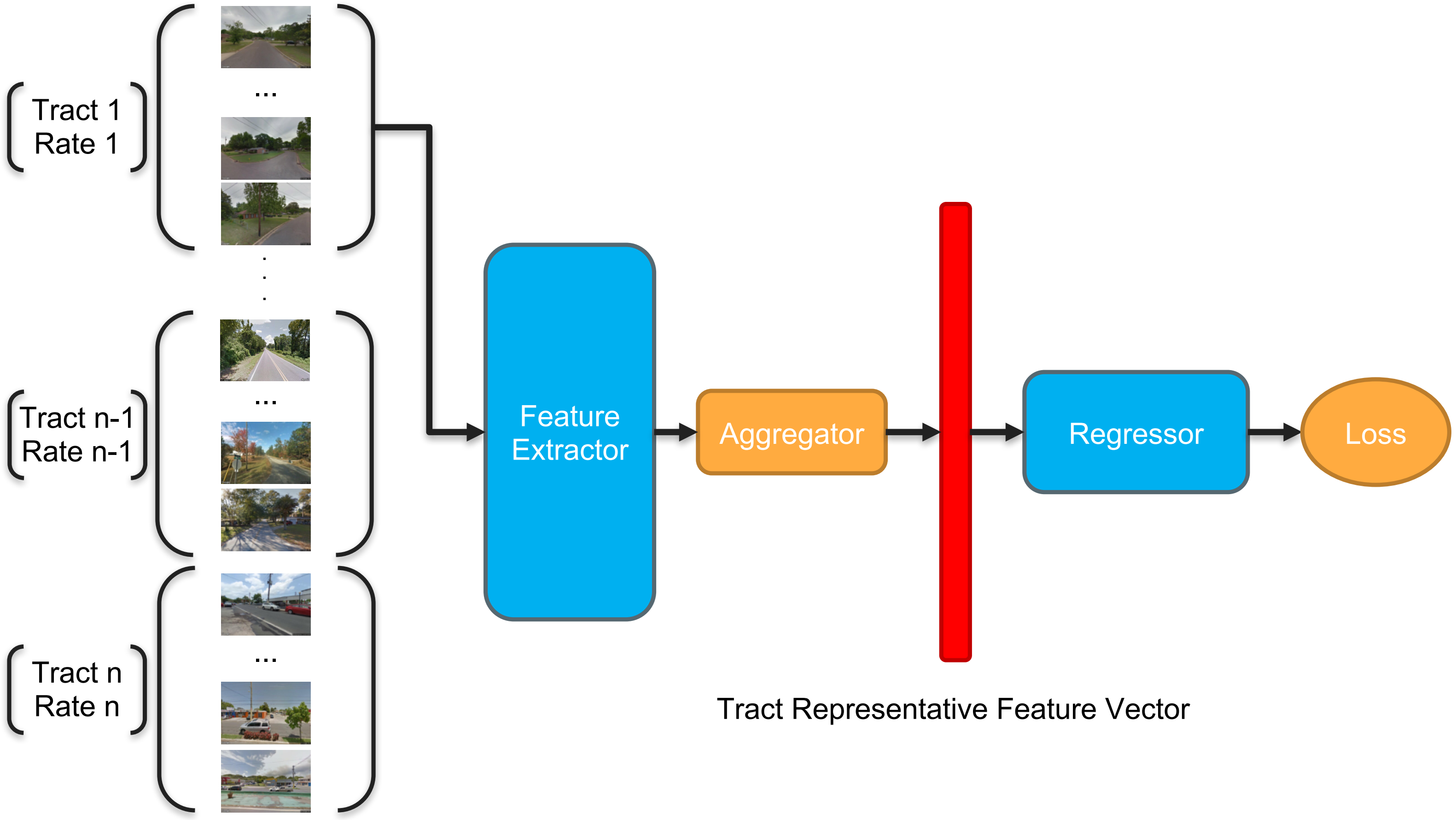
Green30: 1 CrossWalk: 1
Not SFH: 0 Single Lane: 1
3 or more Lane: 0
Visible Wires: 0

The challenge of image labeling

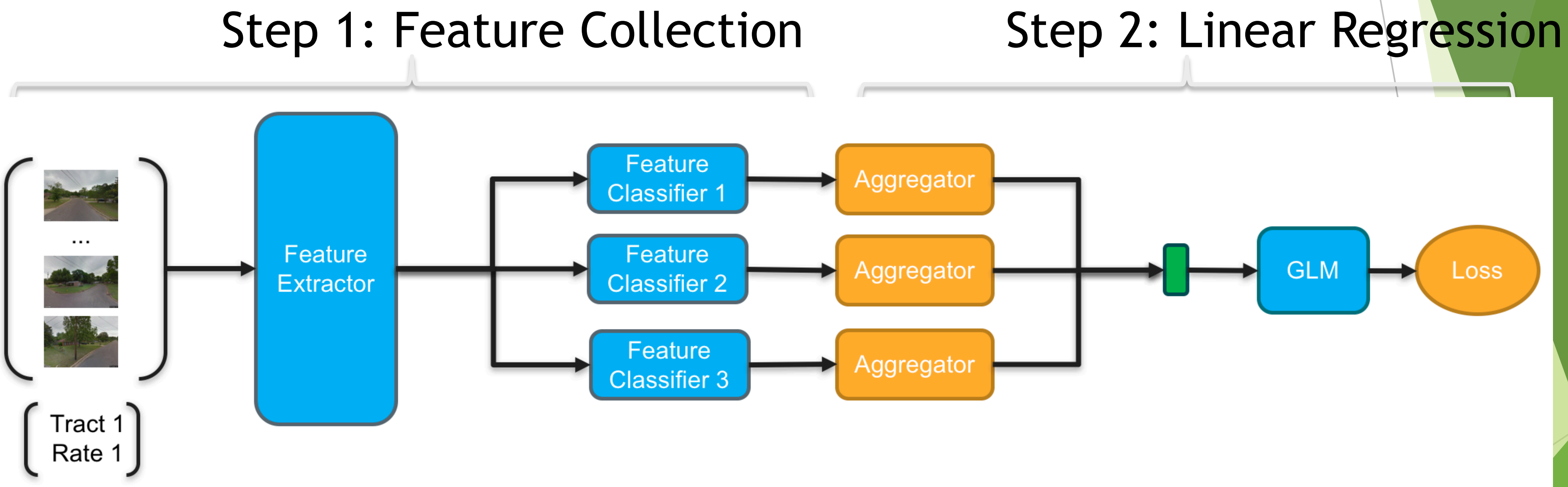
- Due to variation in architecture and landscaping throughout the US, the model needs a much larger annotated dataset to generalize well
- The built neighborhood features approach has the problem of manual labeling per image for classifier training – does not scale up easily
- The designed features (built environmental features) may not be able to capture all the variations in the data
- We propose a direct regression model that obviates the need for manual annotations to find prevalence rates

Direct model: Census tract level regression

- Input: collection of images corresponding to a tract
- Output: chronic disease prevalence
- Freely available supervision: Disease prevalence rates at census tract level
- This network is permutation invariant due to the aggregation block



Baseline model: Regression with built environment features



- Built environment feature extractors are learned from manually labeled dataset
- Regression network aggregates these built environment features at census tract level and learns from disease prevalence ratios
  - Feature extractor model is frozen during regression learning

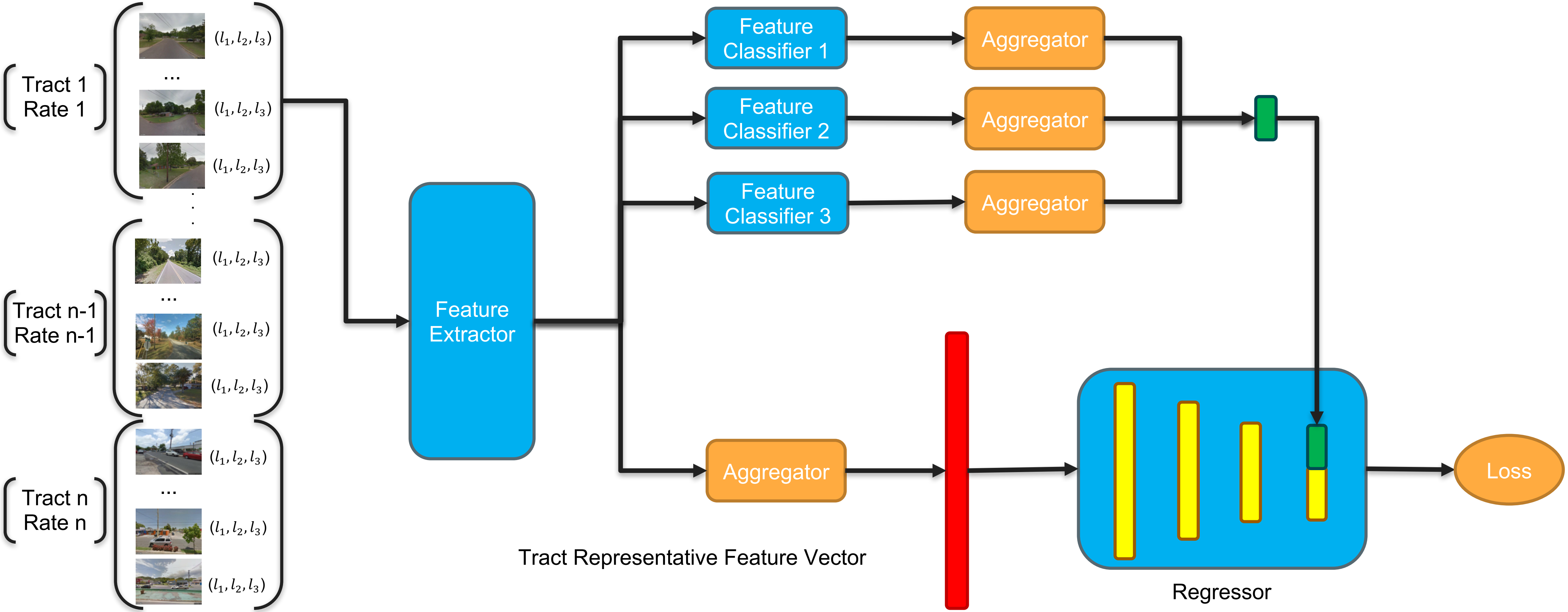
Comparison: Direct Approach vs Baseline model

- 32 million images / 53,921 unique census tracts
- We have disease prevalence rates (obesity rates) for 19,707 tracts (7 million images)
- 5-fold cross validation
- Coefficient of determination R^2 (standard deviation)
  - Baseline regression model: 0.06 (0.0001)
  - Direct regression model: 0.63 (0.0261)

Javanmardi et al, Analyzing Associations Between Chronic Disease Prevalence and Neighborhood Quality Through Google Street View Images, IEEE Access, 2019

Hybrid Model

- Domain experts are interested in correlating built environmental features to disease prevalence rates; however, the direct approach does not provide built environment feature classification
- We propose a hybrid network to simultaneously predict individual image built environmental features and census tract level disease prevalence rates
- We use the regressor network as a regularizer to extract more universal features across the US in order to have a better generalization of the feature classifier

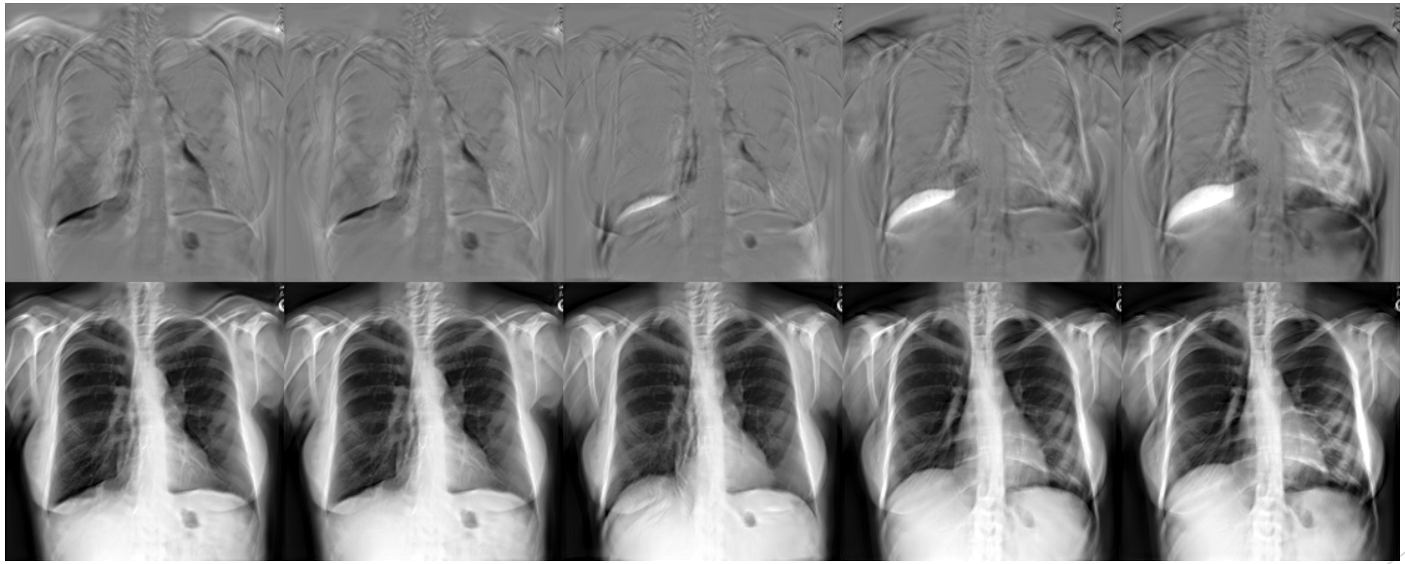

Tract 1
Rate 1
Tract n-1
Rate n-1
Tract n
Rate n
(l_1, l_2, l_3)
...
Feature Extractor
Feature Classifier 1
Feature Classifier 2
Feature Classifier 3
Aggregator
Aggregator
Aggregator
Aggregator
Tract Representative Feature Vector
Regressor
Loss

Results: Hybrid model

- In the hybrid network we utilize multi-task learning where we benefit from two sources of information for training
  - annotated data for built environment classification
  - chronic disease prevalence
- Coefficient of determination R^2 (standard deviation)
  - Baseline method: 0.06 (0.0001)
  - Direct approach: 0.63 (0.0261)
  - Hybrid approach: 0.70 (0.0023)

Conclusion

- November 2019, we collected 170 million images from across the United States
  - Expected date for computer vision indicators: Spring 2020
- Explainable Machine Learning models



Lanfredi et al, Adversarial regression training for visualizing the progression of chronic obstructive pulmonary disease with chest x-rays, MICCAI 2019

Acknowledgements

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