

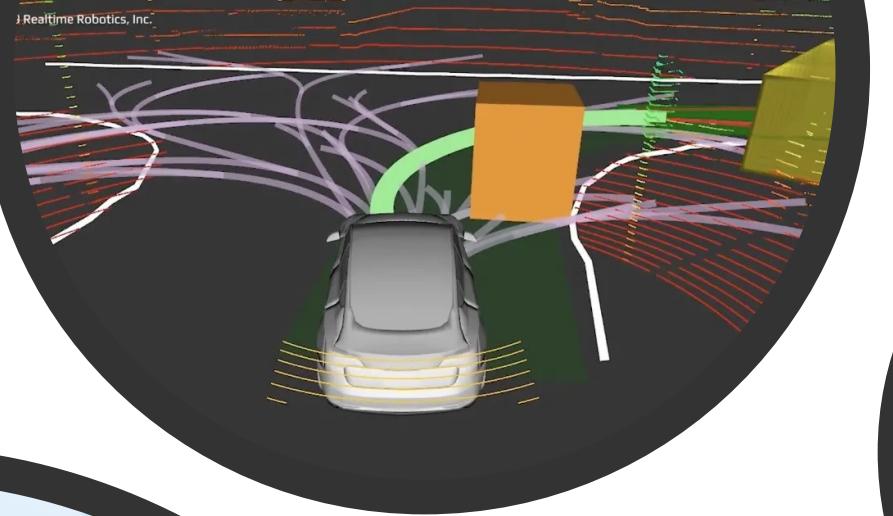


OpenSight: Leveraging Explainable AI for Targeted Congestion Reduction and Pollution Mitigation

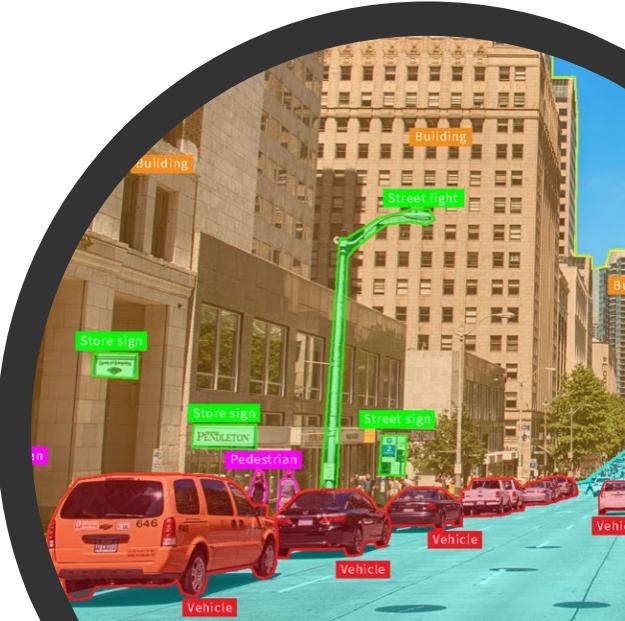
Authors: Vedic Panda, Ish Mehta

Fall 2023

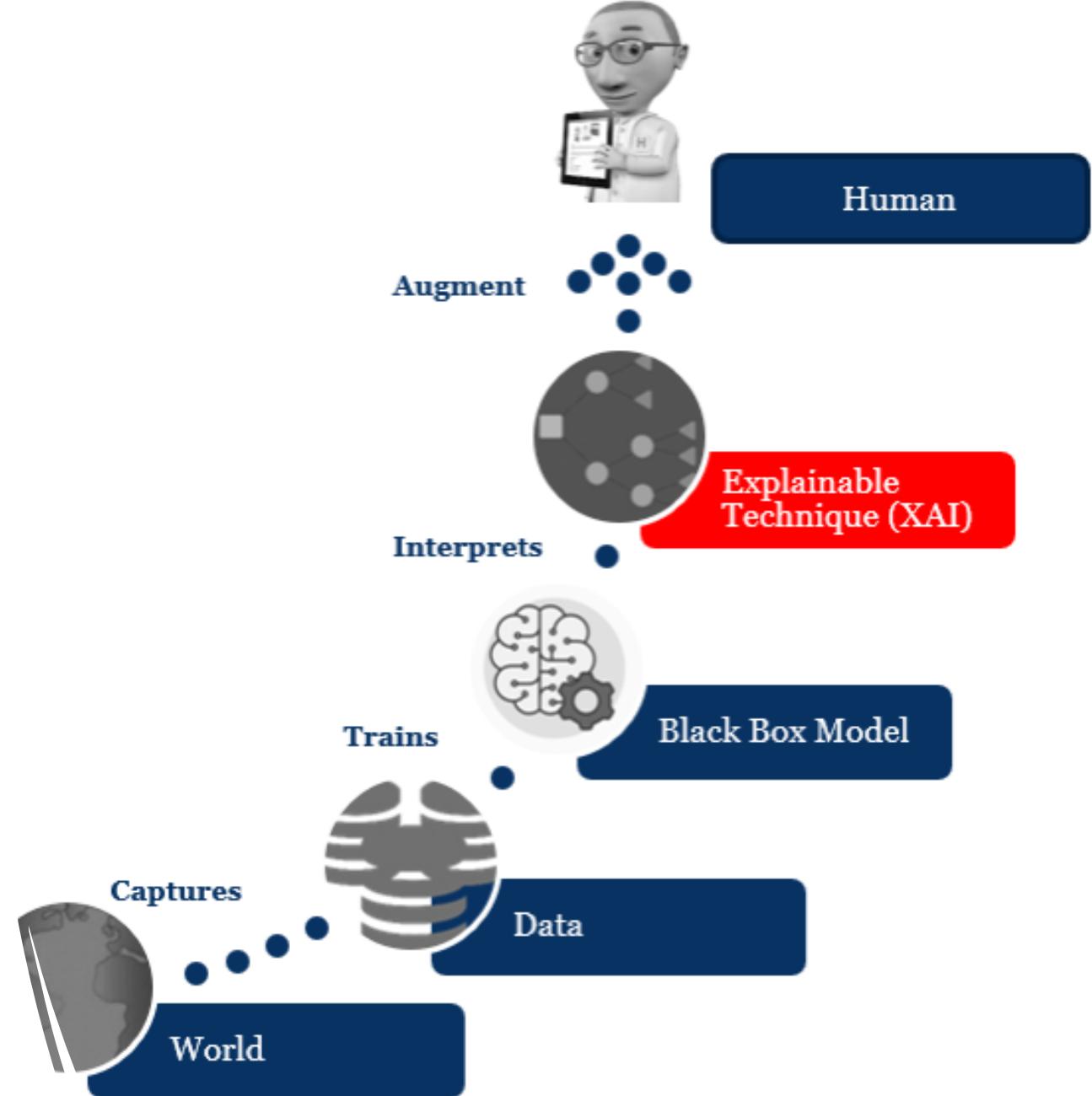


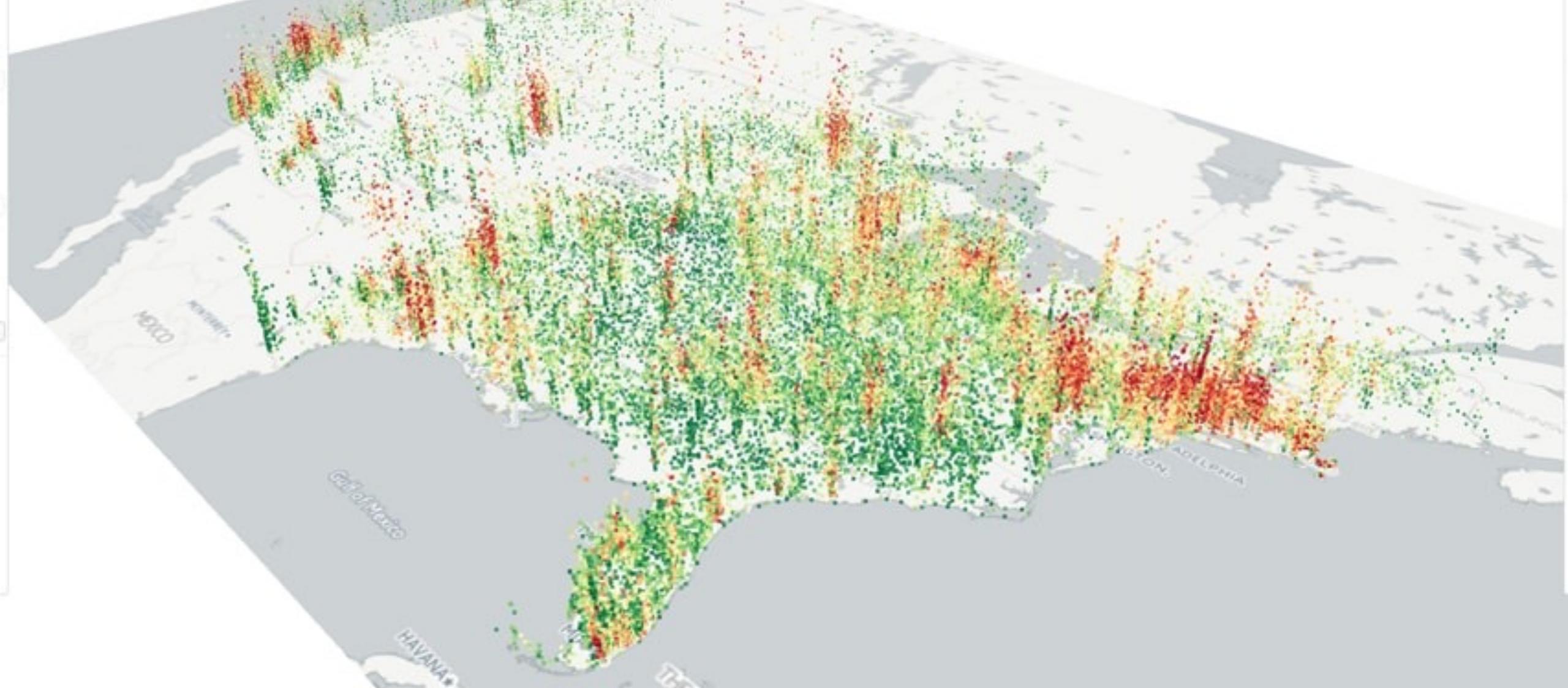


Artificial Intelligence



Issue: AI as a BlackBox. Solution? XAI





Motivation – Complex Datasets

Community needs

Our target audience:

Policy makers for NYC congestion tax, on air quality, traffic volume, and overall urban sustainability.

406,335 Vehicles Enter Manhattan Below 60th Street Every 24 Hours

54,870
Lincoln Tunnel

42,342
Holland Tunnel

29,025
Hugh L. Carey Tunnel

60th St.*

77,649
Queensboro Bridge

46,002
Midtown Tunnel

50,294
Williamsburg Bridge

41,724
Manhattan Bridge

64,429
Brooklyn Bridge



Figma Mockup -
[Link](#)



Approach



Data pre-processing



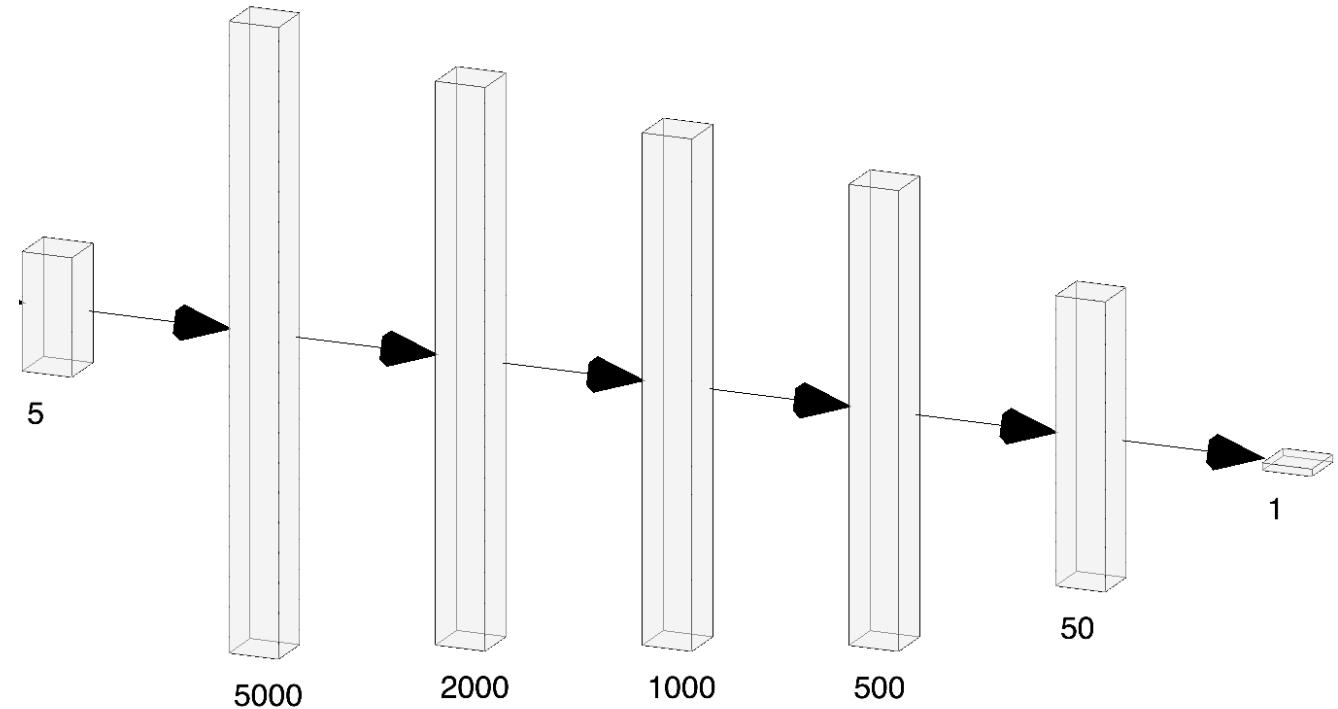
Trained with 5 features
['Annual vehicle miles traveled',
'Annual vehicle miles travelled (cars)',
'Annual vehicle miles travelled
(trucks)', 'Time Period',
'Geo Place Name']

SGD with Batch size of 8

Epochs: 200

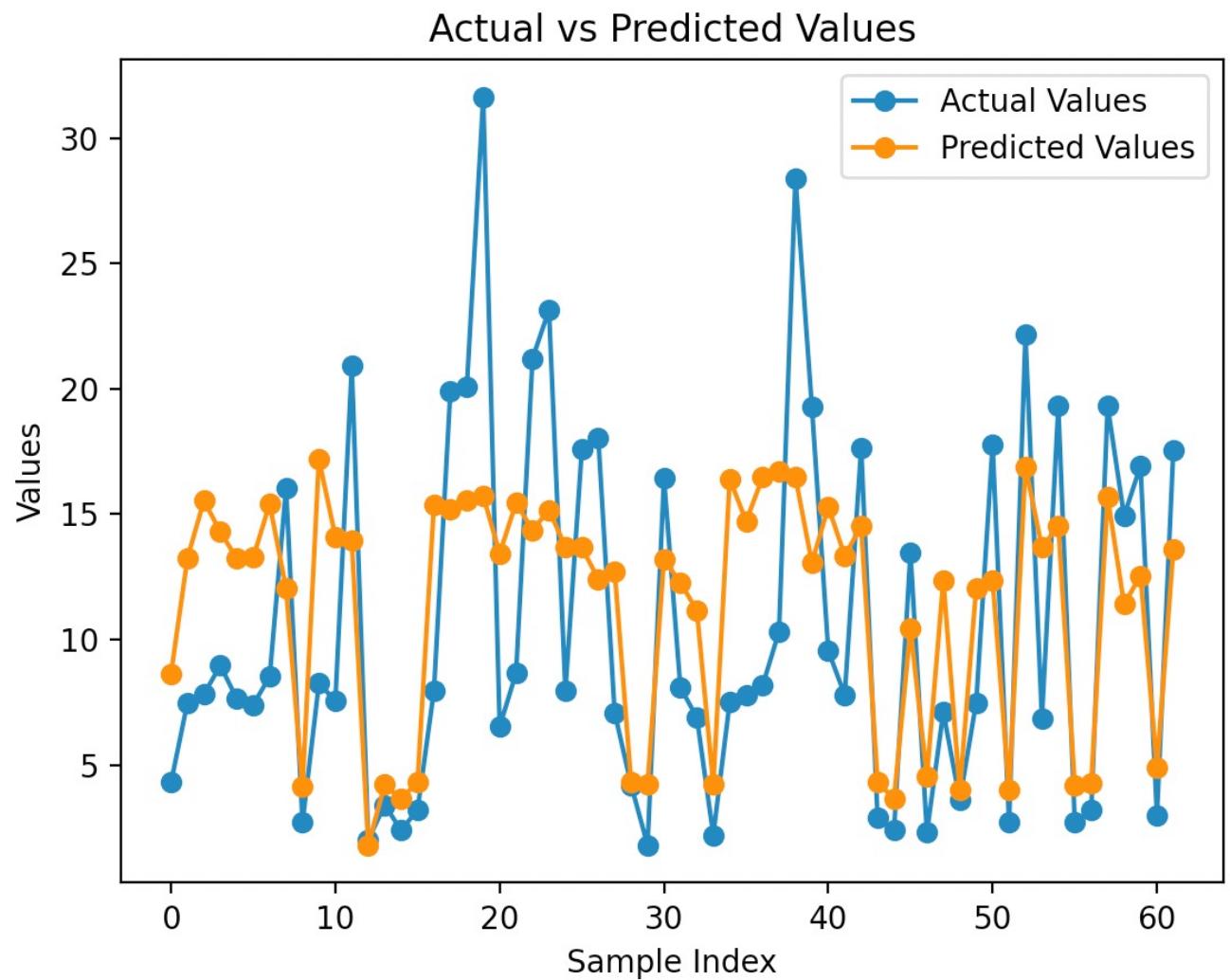
Batch Normalisation after each layer

XAI Model: SHAP



Results – Predicting PM 2.5

- MSE: 31.00
- R-squared: 0.41



Pitfalls



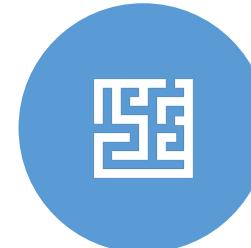
Really small and simple dataset – after preprocessing, we only had 300 datapoints



Lack of consistency in detectors used in the dataset i.E. Pm 2.5, NO2 levels, SO2 levels, asthma levels, air toxics, cardiac deaths

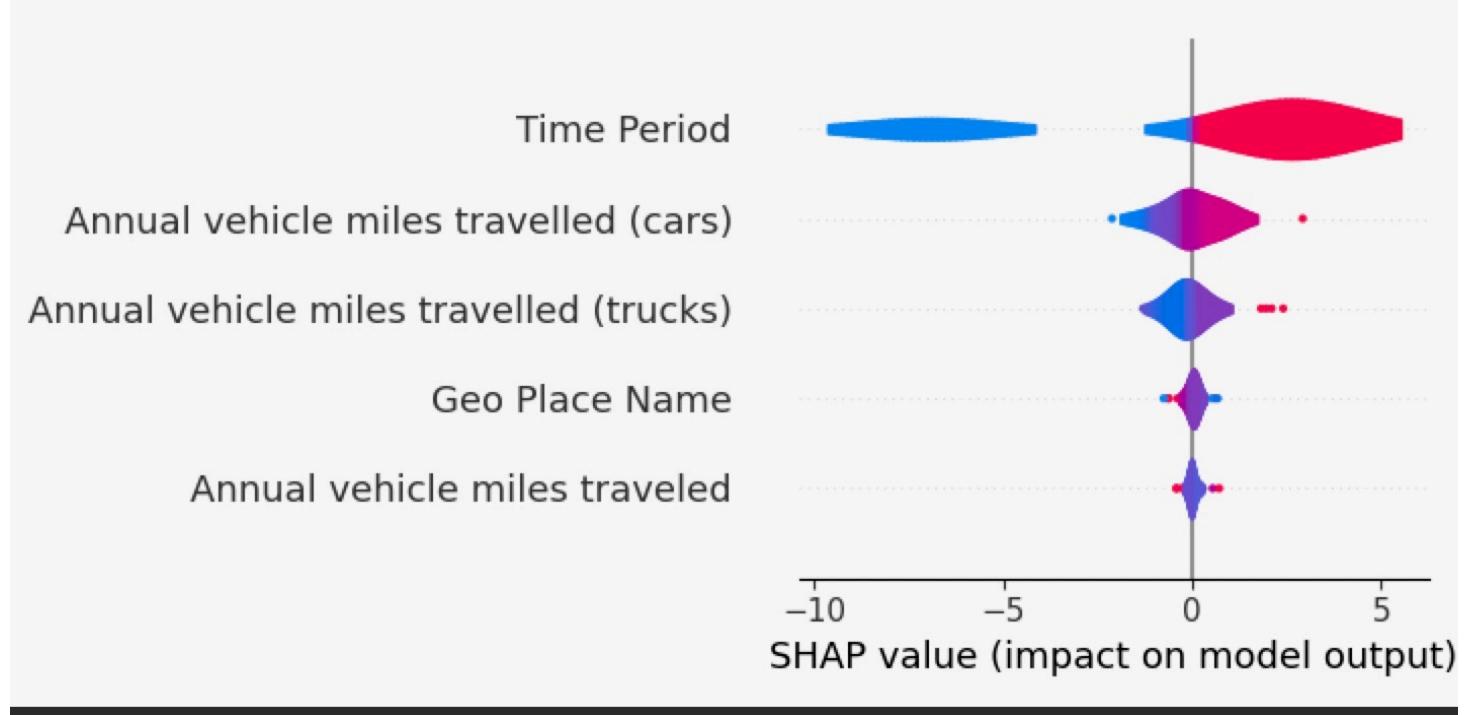


Only able to express 2 years, 2005 and 2016 because we were not able to spend enough time understanding the dataset



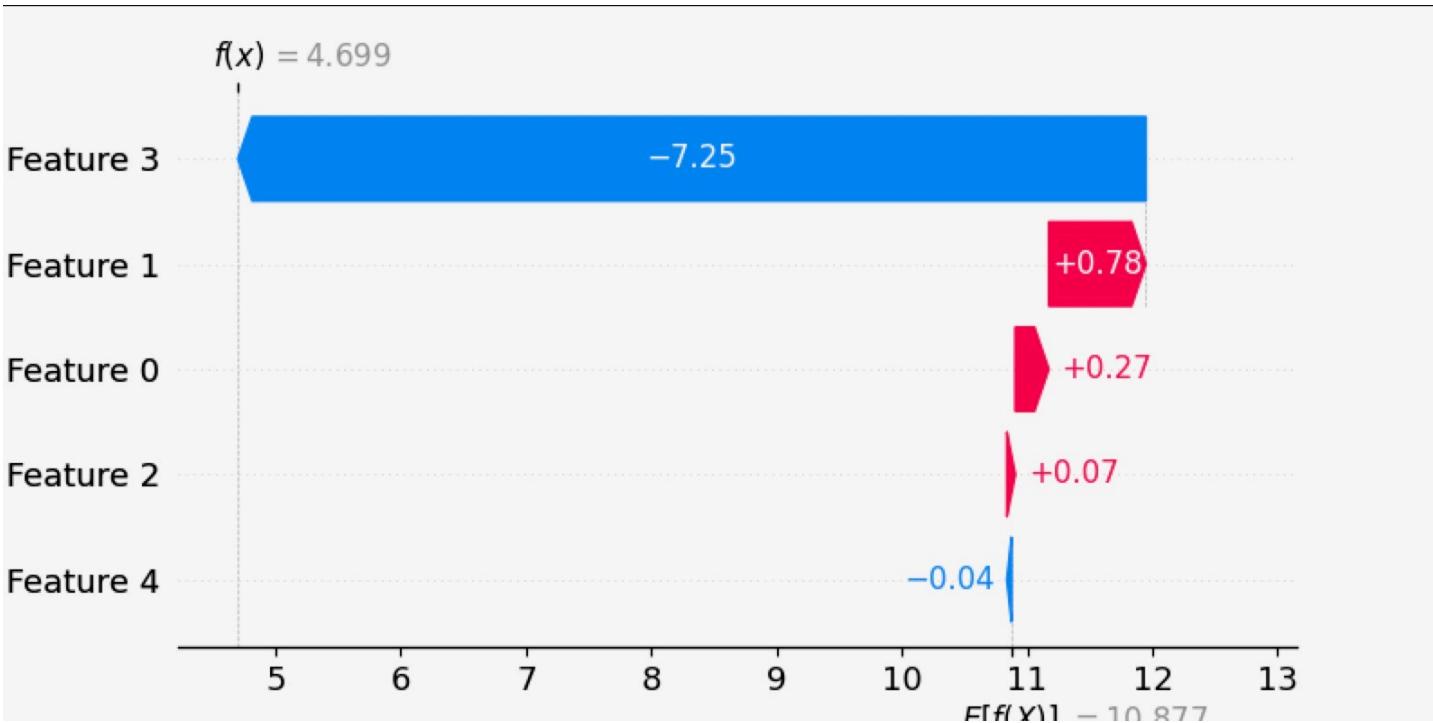
Spent a lot of time (in vain) trying to combine 2 different dataset in the hopes to achieve better data but similar issues arised

xAI Integration - SHAP



- This plot shows how higher and lower values of the feature will affect the result.
- The horizontal axis represents the SHAP value, while the color of the point shows us if that observation has a higher or a lower value, when compared to other observations.

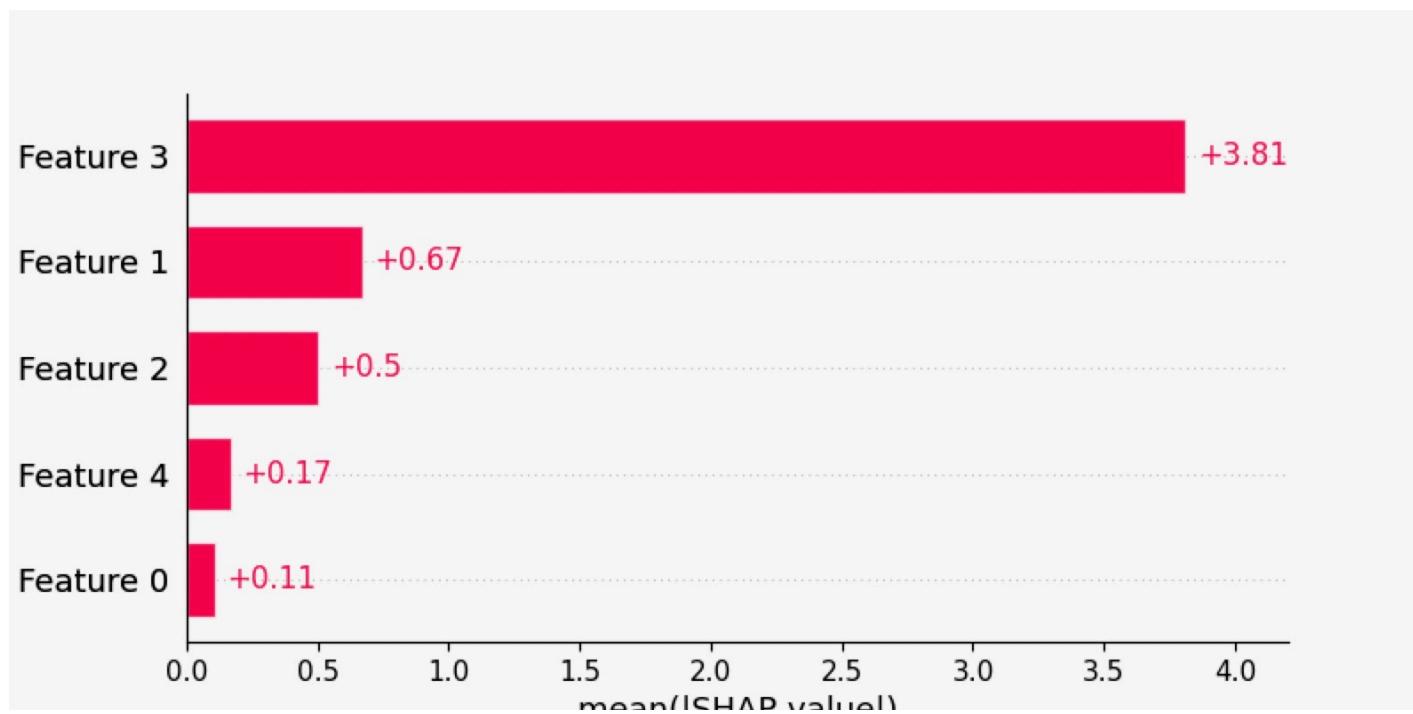
- This plot shows us the magnitude of the SHAP value for each feature.
- The sum of all the SHAP values equals the difference between the prediction $f(x)$ and the expected value $E[f(x)]$.



Feature Legend:

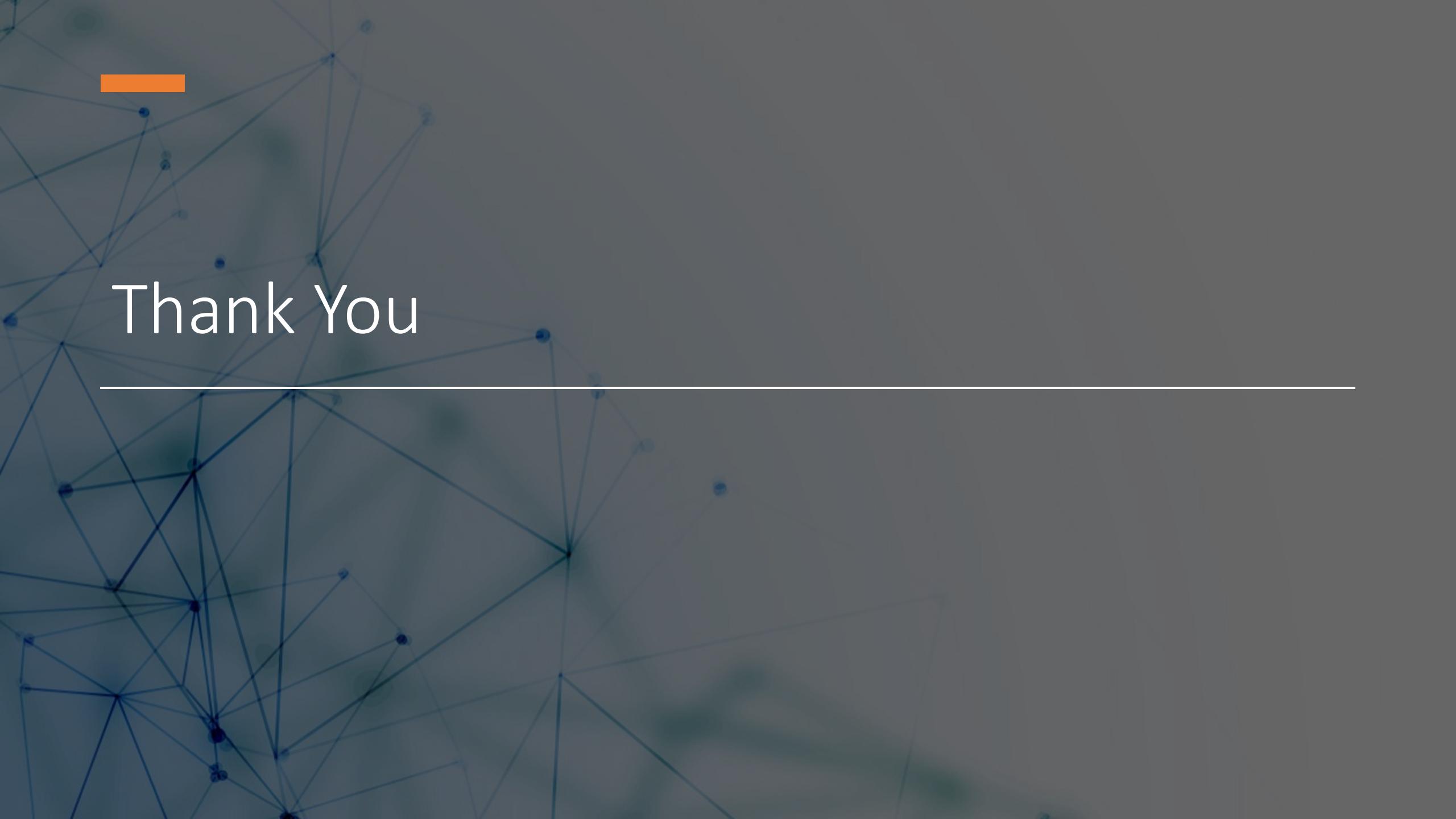
- 0: Annual Vehicles Miles Travelled
- 1: Annual Vehicles Miles Travelled (Cars)
- 2: Annual Vehicles Miles Travelled (Trucks)
- 3: Time Period
- 4: Geo Place Name

- Once our SHAP values are computed, we inputted them in a global feature importance plot
- The global importance of each feature the mean absolute value for that feature, regardless of negative/positive influence
- Features are ordered based on SHAP value (model impact)



Feature Legend:

- 0: Annual Vehicles Miles Travelled
- 1: Annual Vehicles Miles Travelled (Cars)
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- 3: Time Period
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Thank You
