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

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One of the hardest challenges we face today is to tackle the rapidly declining conditions of the Earth's climate caused due to human activities [5]. There are countless efforts being taken everyday to combat climate change which are fueled by gaining a better understanding of the causes of this decline. One such measure is the imposition of the congestion tax in New York City (NYC) [2] with the intent to discourage use of personal vehicles within the city, and encourage the use of more environmentally friendly public transportation. Meanwhile, the use of Machine Learning (ML) algorithms is acknowledged as one of the most well known methods to modelling non-linear environmental changes. Although these ML techniques show promise in modelling such intricate and multivariate scenarios, they are extremely hard to interpret especially since they are black boxed. Explainable artificial intelligence (XAI) can assist in acquiring interpretable insights into the model and enable informed decision-making. This paper proposes applying XAI to congestion modelling to give insights into the effectiveness of the NYC tax.

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1 INTRODUCTION

Over the last few years there has been an increasing trend to leverage Machine Learning techniques, specifically Deep Learning, for high stakes prediction applications that deeply impact human lives. The techniques have rich expressive power comparable to and sometimes even surpassing human cognitive abilities in many tasks. It is vital to use such techniques when it comes tackling high-stake problems such as climate change especially when we are dealing with cases such as the one we are tackling in this paper. With the ease of access to sensor data collection, we have extremely larger and complicated data sets that are based on time and location. Analysing these data sets can be really complicated. Having a deep learning model learn the data and the important features, with the intent of prediction are the first steps towards leveraging ML models.

However, this expressive capabilities by itself comes at a cost which is extremely expansive inferencing [9]. Since the inference process of deep learning algorithms is regarded as a black box, it is extremely difficult if not impossible to deduce the impact that each parameter has on the model. This is where XAI comes in. XAI is rapidly emerging field in AI that aims to provide human-understandable justifications for a system's behaviour [4]. Thus, if we were to have a deep learning model learn the data (with the intent of prediction through regression) and then apply an XAI algorithm such as SHAP to give insights onto the features that the model finds most important, can give great insights into complicated data sets.

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2 BACKGROUND

There are several XAI techniques that are widely used for different ML techniques. For instance for deep networks, the two widely used are Local Interpretable Model-agnotic Explanation (LIME) [11] and Shapely Additive Explanations (SHAP) [8]. LIME explains models using a local linear approximation and outputs values indicating the contribution of each explanatory variable to a given inference. SHAP also outputs the importance of each explanatory variable for the inference using Shapley values based on game theory. Meanwhile, for CNNs Gradient Weighted Class Activation Mapping (Grad-CAM) [12] is a widely used model that is based on gradient calculation of each convolution layer.

3 RELATED WORKS

The idea of a tool this paper proposes is really important to the community as it brings the power of AI to everyone's hands and allows the community and those concerned about it to make the own analysis. There are several papers that do this analysis themselves but there are certain gaps that we intend to fill. The existing approaches can be seen in the Ming Cai et al [3] and Christer Johansson et al [6]. As seen in Ming Cai, it does a very similar analysis of air pollution concentrations however there was a very tedious data collection step which took place around one street in Guangzhou, China. For such an analysis to take place at a bigger scale, one can imagine the amount of effort required especially for someone who does not have access to such resources. However, most large cities already have large data sets which can be utilised. To do so, we want to leverage XAI tools mentioned previously in section 2. Moreover, as seen in Christer Johansson et al The Stockholm trial they conducted was a very tedious way of collecting data and spanning a very short period of time of only 6 months. It also required a very comprehensive set of dispersion modelling to achieve results.

It is important to note, we are not trying to replace these detailed analysis, instead we are trying to compliment it by enabling the user to provide a better insight in to the data set. For instance, One earlier study, Tonne et al [7] has assessed the effects of a charging scheme not only on traffic and emissions, but also on exposure concentrations and health. They used a combination of dispersion modelling and regression calculations to analyse the air pollution and mortality benefits of the London congestion charge scheme (CCS). For modelling emissions, they use two emission models such as CMEM which is considered to be a living model. Which means, while it was created in 2008, the model needs to be updated to reflect the fleet of cars at the time. However, there are various other factors that change which the model does not measure. One such example for instance are the effects of public transportation on emissions. These gaps that the current models have is what we are trying to give insights into by having a deeper understanding of the data which can compliment results from these models.

Furthermore, we found a paper by Mehrad Arashpour [1] that focuses on the importance of XAI for environmental research. It proposes a CNN framework with a custom XAI implementation. We try to follow its path but with a MLP model.

4 COMMUNITY NEEDS/ASSETS

We propose to help the state of New York make an informed decision about the introduction of the congestion tax[2]. With the rising amounts of air pollution in the city, a new congestion tax, similar to the one in London as been suggested, where you are charged some amount for driving through the city. The goal is to motivate people to use more sustainable forms of transportation within the city, thus reducing the amount of air pollution. The question then arises, how much impact would such a policy have? Would the reduction in pollution be measurable or is the impact of vehicles not as impact-full as once thought? These are some of the questions we want to answer, through our pipeline.

The intended community are the urban planners and policymakers. This paper is designed to empower them with data-driven insights to make informed decisions regarding urban sustainability. They can leverage the platform to assess the impact of various policies and initiatives, such as congestion charges, on air quality, traffic volume, and overall urban sustainability. As seen from the related works, this community does have quite a technical knowledge, but not necessarily programming knowledge. Thus, our attempts to create a generalisable XAI framework intended to make the learning curve less steeper for them.

5 IMPLEMENTATION AND EVALUATION

5.1 Dataset and Pre-preocessing

Based on this paper's objective, the data set needs to represent the pollution levels and the vehicle density/count based on the time period and area it is in. The bigger the area and the larger the time period we can cover, the better understanding the model will have. We have chosen to work with the following data set. **Air Quality Data Set (DOHMH) [10]:** This data set contains air quality measurements and health-related information across various neighborhoods in New York City. We will use air quality indicators, such as PM2.5 levels, to assess the quality of air in different areas over time. It also contains the counts for the number of miles travelling annually by vehicle type. This data is essential for understanding the baseline air quality situation in the city. To do so, the data set was pre-proceesed as follows:

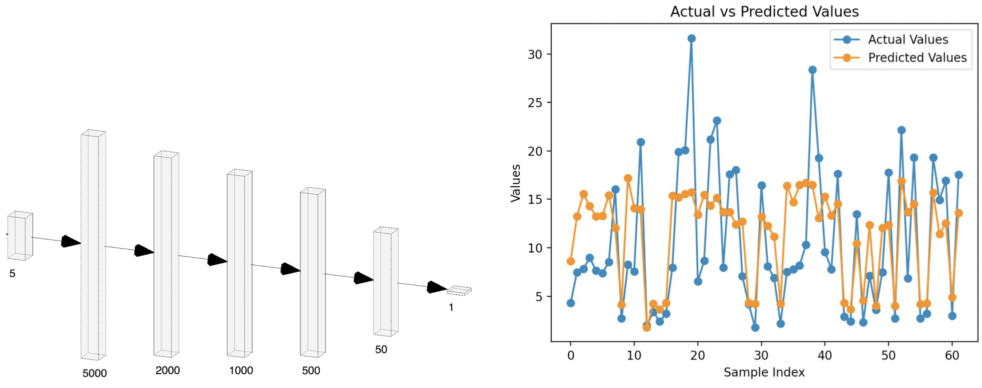
- Extract information based on common features. A curated list of relevant indicators to be used is established, encompassing elements such as 'Annual vehicle miles traveled,' 'Annual vehicle miles traveled (cars),' 'Annual vehicle miles traveled (trucks),' and emissions from boilers, specifically 'Total SO_2 Emissions,' 'Total PM2.5 Emissions,' and 'Total NO_2 Emissions.'
- Create features that describe the presence or absence of congestion charges based on the implementation timeline for New York City. This is represeted in a Pandas Dataframe
- Utilize time-series data to study the impact of congestion charges on traffic volume and air quality over time.

5.2 Deep Learning Model

The proposed approach was to make a simple fully connected neural network with 1 hidden layer, as shown in (Ming Cai et al) [3]. This model will be trained in the data set described previously. However, to increase the accuracy of the model we quickly adapted to a much larger DL model with 5 hidden layers and approx. 8.5K parameters. The architecture and model details can be seen in Figure 1 (a). Trained 200 epochs with SGD and a batch size of 8, to estimate PM 2.5 levels, we get a MSE of 31.00 and a R-squared value of 0.41. While these results are not the best, they do capture the general trend of the data as seen in Figure 1 (b) (we will explore the reasons for the model accuracy later in the paper). The results are as follows because A SHAP XAI model will then be used to analyse our neural network and describe the effects of each feature.

5.3 XAI Implementation

For the purposes of this paper, we decided to implement SHAP as our choice of XAI model due to its simplicity and ease of access. Before we go on, lets go over what SHAP is. It is an ingenious solution originating from game theory to open these black boxed AI models. SHAP distributes attribution credit among features contributing towards a model output. Each input vector gets assigned a SHAP value quantifying its positive or negative impact on the forecast. Reducing predictions see negative values, while increased forecasts receive positive SHAP scores. These granular scores easily



(a) (b)

Fig. 1. (a) Deep learning model with 5 hidden layers - Batch Normalisation after each layer; size of each layer can be seen in picture. (b) Graph representing actual vs predicted values.

visualize as plots, with factors strongly driving modeled projections clustered based on their attribution magnitudes and directions.

In essence, SHAP builds trust in predictions by grounding them in explainable features policymakers grasp. The technique brings transparent rigor to multiplying AI systems, ensuring algorithms amplify rather than replace human judgment at the helm of environmental progress.

For this paper, we run the SHAP algorithm on the DL model we trained earlier to get the results shown in Figure 2. Figure (a) is the waterfall prediction plot that the emission contributions from various transportation data inputs. As seen in the graph, the time period feature has the most significant impact in most cases. Other features boast a more evenly distributed influence, meaning that the patterns that can be extrapolated from the data are a bit less useful. Repeated patterns across instance plots for a more detailed data set would reveal if certain vehicle types, years, or geographies contribute more to pollution projections consistently. Policy analysts can then respond with tailored vehicle emission interventions targeting the features indicated most environmentally influential by the interpret-able model.

Figure (b) is the local SHAP bar plot that focus exclusively on explaining one model prediction and how feature values for that specific input contributed. It attributes the output to the unique real-world attributes present in just that instance. Local SHAP bars simplify to show only magnitude with all values aggregated as absolute contributions. As seen in the graph, it is apparent that Feature 3 mainly has a negative magnitude affect on prediction values while all other features except for Feature 0 have a positive influence. This indicates that there is some sort of direct correlative relationship between vehicle miles traveled across cars and and trucks while, there is some sort of inverse relationship between prediction power and time period. This plot can be extremely useful in analysing outliers and finding patterns between outliers.

Figure (c) provide overall feature importance rankings based on average absolute contribution to model output levels across a full dataset. They summarize which features are influencing predictions more versus less, irrespective of positive or negative direction. In our case it can be extrapolated that for our model predictions Feature 3 (Time period) had a much higher impact, with it being followed by Features 1, 2, and 4. Meanwhile Feature 1 (miles travelled by cars)

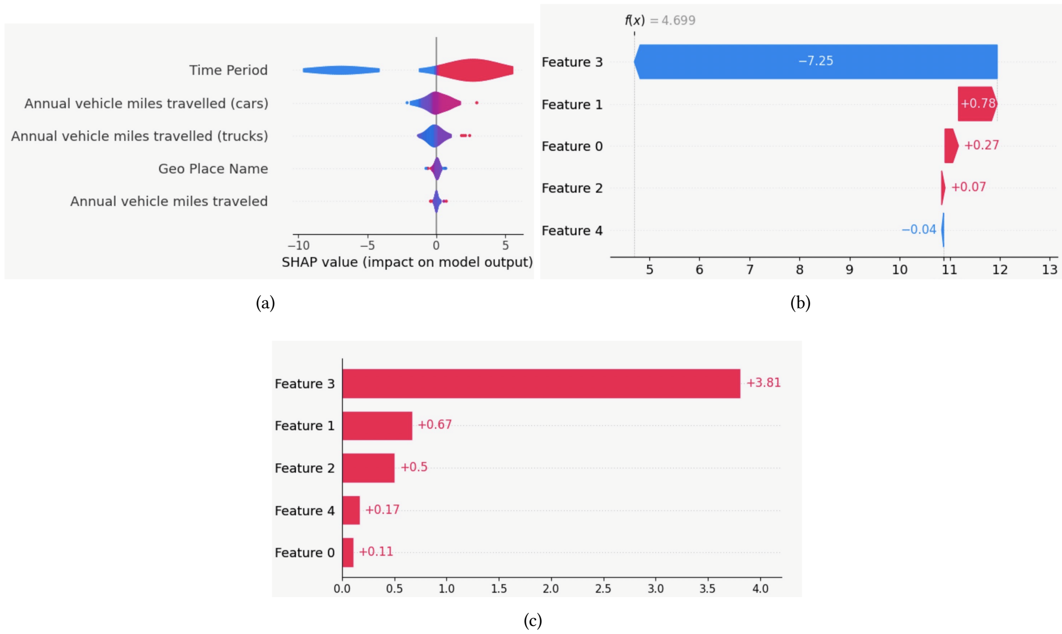


Fig. 2. (a) Feature Importance by Observation (b) SHAP magnitude per feature (c) Global Feature Importance;
Legend- 0: Annual Vehicles Miles Travelled, 1: Annual Vehicles Miles Travelled (Cars), 2: Annual Vehicles Miles Travelled (Trucks), 3: Time Period, 4: Geo Place Name

has more importance than Feature 4 (miles travelled by truck) which means that the biggest contributor between those two are cars, thus imposing a higher tax on trucks would not lead to a favorable outcome.

6 LIMITATIONS

There were several major limitations encountered during this project. Most of which relate to the data set and pre-processing. As mentioned earlier, our DL model was not too accurate. This mainly due to the lack of useful training data we had access to. Despite the original data set we chose having millions of data points (which or a deep learning model of this size is more than enough), the number of data points left after we did our required pre-processing steps were only 300 data points. This drastic reduction in data stems from the lack of consistency in detectors used in the data set i.E. Pm 2.5, NO2 levels, SO2 levels, asthma levels, air toxins, cardiac deaths are used inter-changeably. Moreover, the vehicle information which we sought for was only available for two years, 2005 and 2016. Put together, training the network was quite challenging. While the network was able to capture the general trend, for these two year, our intuition is that it will perform terribly for unseen data and for years it has not yet seen. We could have gotten better results, but that would require a lot of time to combine multiple data sets. Our hopes are that the intended audience for this project has access to more and better data sets than we do.

7 FUTURE WORK

Apart from improving on the limitations we faced, another important are to focus on is the choice of XAI algorithm. It is vital to focus on implementing a framework that is a non-trivial departure from the trend in existing XAI methods, especially SHAP and its variants, which mainly emphasize output explanations. [1]

Furthermore, our vision is to create a generalise-able open source framework to allow this same workflow to be used for custom data sets in a broad range of scenarios. A figma mockup (**Link:** https://www.figma.com/file/shO3D6uucWPRrNmpUELZlc/Untitled?type=design&node-id=0%3A1&mode=design&t=57rBb9z30mEDas9S-1) was created to envision our proposal. The landing page provides a glimpse into our product, offering a brief introduction and an immediate option to start using it. Users can choose from a selection of datasets to train their machine learning model, initially limited to three dummy datasets for simplicity. The interface guides policy makers, our target users, through model selection, providing simple explanations for each. After selecting a model, users can simulate the backend training process and explore insights, including feature rankings based on SHAP values. Clicking on a feature provides LLM-generated suggestions for potential actions. For a more detailed view, users can click on the see stats button to explore actual values and feature rankings.

Some thought was also put into the idea of seeing whether or not policy makers would like to use LLM generated text to come up with ideas for potential policies and reforms. However, we believe most policymakers would actually prefer outputs beyond solely LLM-generated text given a few key factors:

Actionability - Policymakers ultimately need to make decisions that lead to progress. Raw text alone often lacks specific recommendations or quantitative insights required to inform viable new rules, investments, interventions, etc. Interactive visuals, highlighted data subsets, or summarized regulatory options tailored to one's jurisdiction may prove more directly actionable.

Credibility - Veteran policy experts are accustomed to sourcing guidance from trusted institutions and peer-reviewed science rather than raw AI text which may seem speculative. Backing suggestions by citations, expert testimonials, or even an interactive interface to adjust assumptions could go far.

In essence, purpose-built interactive tools co-designed with policymakers themselves will likely be embraced most - with LLM text as a supplemental generator rather than primary work output.

At its heart, this conceptualized product aims to eliminate the technical obstacles inhibiting policy teams from leveraging sophisticated machine learning to illuminate and predict key trends, relationships and interventions across pressing pollution and environmental health challenges.

8 CONCLUSIONS

In conclusion, our proposal introduces an ambitious yet practical open-source platform that combines the power of machine learning (ML) with Explainable AI (XAI) to enhance decision-making processes. Focused initially on addressing the congestion tax debate in New York City, our approach integrates datasets on traffic volume and air quality, employing a deep learning model. The application of SHAP XAI allows for a nuanced understanding of the model's dynamics, shedding light on the impact of congestion charges on traffic flow and air quality.

REFERENCES

[1] Mehrdad Arashpour. 2023. AI explainability framework for environmental management research. *Journal of Environmental Management* 342 (2023), 118149. https://doi.org/10.1016/j.jenvman.2023.118149

[2] Erica Brosnan. 2023. What you need to know about NYC congestion pricing. https://ny1.com/nyc/manhattan/transit/2023/10/02/what-to-know-about-congestion-pricing-in-new-york-city

[3] Ming Cai, Yafeng Yin, and Min Xie. 2009. Prediction of hourly air pollutant concentrations near urban arterials using artificial neural network approach. *Transportation Research Part D: Transport and Environment* 14, 1 (2009), 32–41. https://doi.org/10.1016/j.trd.2008.10.004

[4] Upol Ehsan, Koustuv Saha, Munmun De Choudhury, and Mark O. Riedl. 2023. Charting the Sociotechnical Gap in Explainable AI: A Framework to Address the Gap in XAI. *Proceedings of the ACM on Human-Computer Interaction* 7, CSCW1 (apr 2023), 1–32. https://doi.org/10.1145/3579467

[5] Bohao He, Yanghe Zhao, and Wei Mao. 2022. Explainable artificial intelligence reveals environmental constraints in seagrass distribution. *Ecological Indicators* 144 (2022), 109523. https://doi.org/10.1016/j.ecolind.2022.109523

[6] Christer Johansson, Lars Burman, and Bertil Forsberg. 2009. The effects of congestions tax on air quality and health. *Atmospheric Environment* 43, 31 (2009), 4843–4854. https://doi.org/10.1016/j.atmosenv.2008.09.015 Urban Air Quality.

[7] Zhang K and Batterman S. 2013. Air pollution and health risks due to vehicle traffic. (2013). https://doi.org/10.1016/j.scitotenv.2013.01.074

[8] Scott Lundberg and Su-In Lee. 2017. A Unified Approach to Interpreting Model Predictions. arXiv:1705.07874 [cs.AI]

[9] Shin nosuke Ishikawa, Masato Todo, Masato Taki, Yasunobu Uchiyama, Kazunari Matsunaga, Peihsuan Lin, Taiki Ogihara, and Masao Yasui. 2023. Example-based explainable AI and its application for remote sensing image classification. *International Journal of Applied Earth Observation and Geoinformation* 118 (2023), 103215. https://doi.org/10.1016/j.jag.2023.103215

[10] Department of Health and Mental Hygiene (DOHMH). 2022. Air Quality: NYC Open Data. https://data.cityofnewyork.us/Environment/Air-Quality/c3uy-2p5r

[11] Marco Tulio Ribeiro, Sameer Singh, and Carlos Guestrin. 2016. "Why Should I Trust You?": Explaining the Predictions of Any Classifier. arXiv:1602.04938 [cs.LG]

[12] Ramprasaath R. Selvaraju, Michael Cogswell, Abhishek Das, Ramakrishna Vedantam, Devi Parikh, and Dhruv Batra. 2019. Grad-CAM: Visual Explanations from Deep Networks via Gradient-Based Localization. *International Journal of Computer Vision* 128, 2 (oct 2019), 336–359. https://doi.org/10.1007/s11263-019-01228-7