

Road Traffic Accident Prediction

CSE6242 Data Analytics and Visualization, Georgia Institute of Technology

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Motivation

What is the problem?

Transport authorities worldwide implement strategies to minimize road traffic accidents (RTA). Despite their best efforts, RTAs have not significantly decreased significantly due to the difficulty in predicting when and where RTAs will occur.

Why is it important?

Road Traffic Accidents are a major cause of death globally, leading to a staggering 1.25 million deaths and **50 million injuries** every year.

Objectives

- 1) Build a classification model to accurately *predict the* probability of road traffic accidents in London
- 2) Create an *interactive* and *user-friendly* application for the public to use our model to inform their driving decisions.

Limitations of current practice

- Some models predict where but not when accidents will occur (*Wang et al.)
- Some models are built using limited datasets that yield poor accuracy (*Sun et al)
- Studies focus which features are correlated with traffic accidents, not accident prediction (*Sager et al.)
- Inaccessible to the public: the majority of studies publish their findings in subscription journals in technical jargon. *one of many examples analyzed in this study

Dataset

Road traffic collisions dataset

- A comprehensive dataset of RTAs in the UK from 2000-2016 (discontinuous)
- Data collected and hosted by UK Dept of Transport
- Compiled data available on Kaggle: 1.6 million accident records x 32 features
- Features include:
 - location: latitude/longitude coordinates
 - date and time weather conditions

UK Historical Weather records

- Hourly readings from 2012-2014
- Darksky.net API
- Data collected: 26 thousand data points by 22 weather features

Air pollution Data

 Approximately one thousand rows of daily reading of +5 air pollutants









Building a predictive model

Accident "hotspots" were determined using ArcGIS DBSCAN.

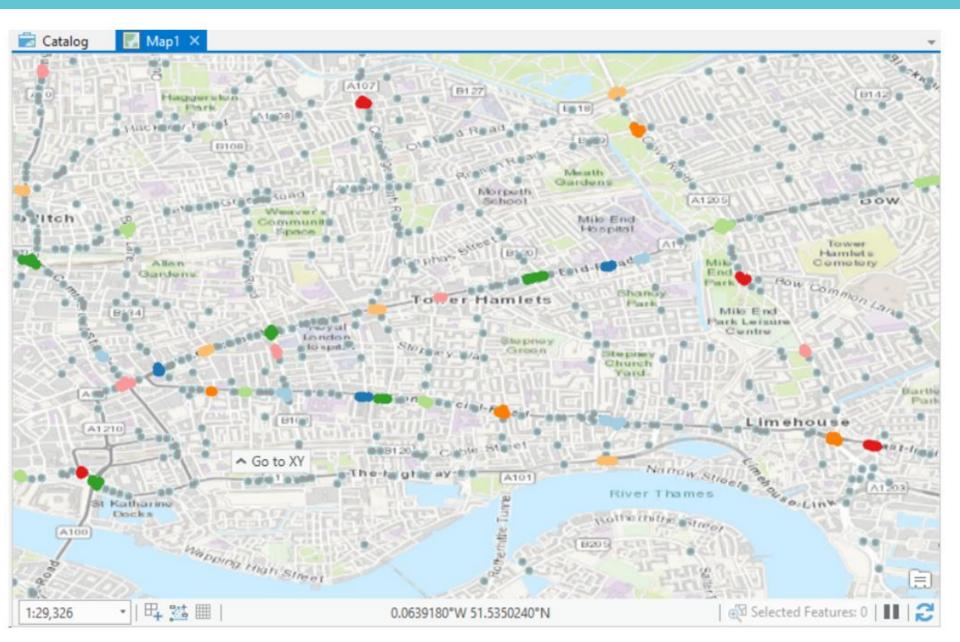
Clustering accident points to reduce noise

Hotspots are considered traffic accident signal, while accidents away from these clusters are more likely random and are considered noise (Francello et al.). A total of 473 'hotspots' clusters were generated.



Generating negative data points

Our accident dataset only contains positive data points (i.e. label = 0). Similar to Yuan et al., for every data point within a cluster we randomly changed the day, year, and/or hour. Three negative data points were created per positive data point.



Building and evaluating a predictive model

We test several algorithms to build our model and found that the random forest model using only numeric features resulted in the highest accuracy (0.83) and AUC (0.87). Therefore, we have chosen to use this model for prediction in our web application.

	No. features	Accuracy	AUC
Random forest (numeric)	<i>25</i>	0.8347	0.8705
Random forest (one-hot-encoding)	23	0.7865	0.499
Logistic regression	25	0.7611	0.6753
Support Vector Machine	21	*ND	*ND

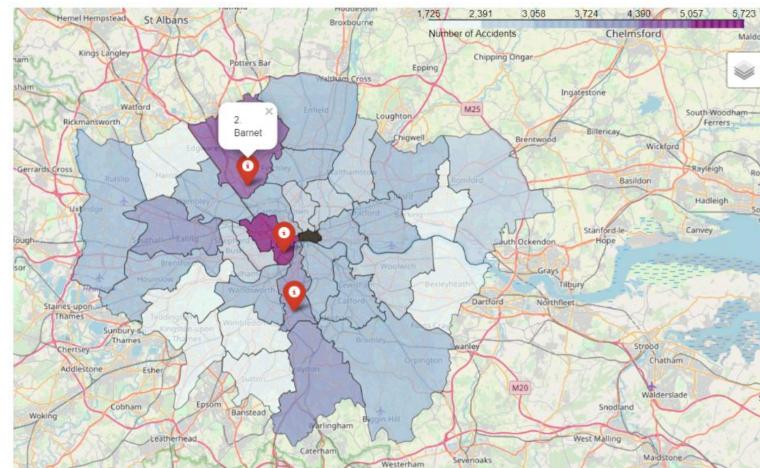
'Not determined (ND). SVM model was stopped after running for two hours.

Implementation of an interactive web application

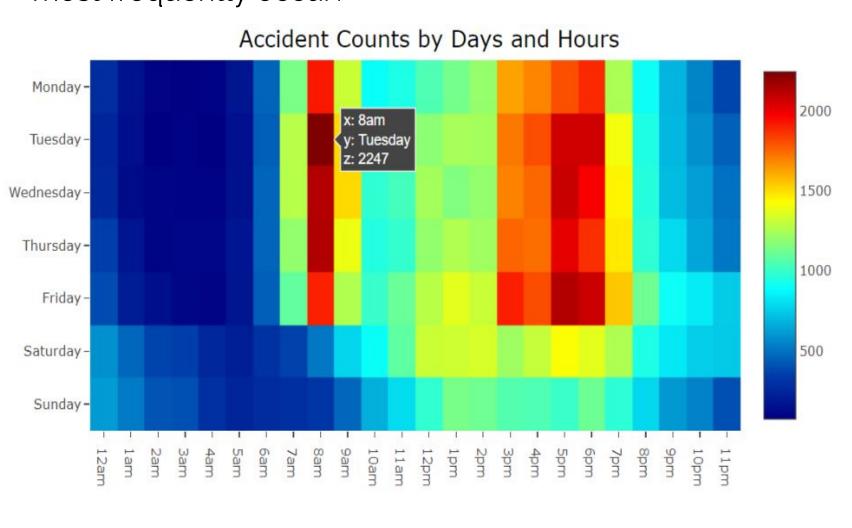
The Interactive Road Traffic Accident Prediction App

The *Exploration* section will take users through a story-line analysis of the traffic data. These visuals will answer questions such as:

Which boroughs in London have the most and least number of traffic accidents?

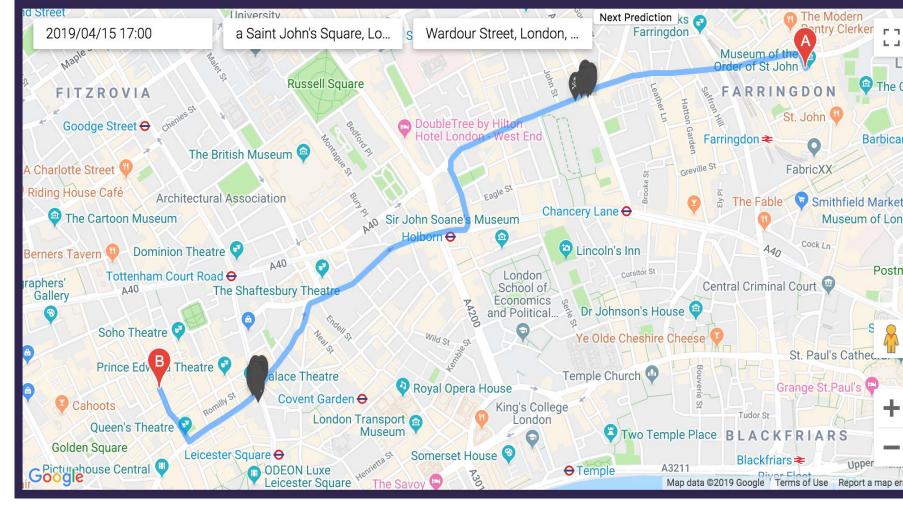


Which times, days, and months do traffic accidents most frequently occur?

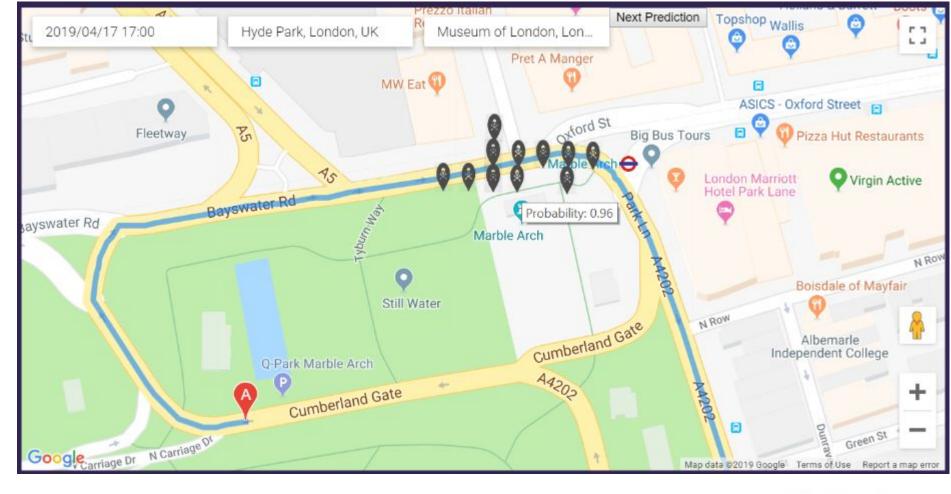


The *Interactive* section contains an interactive map where users input their start and end location within London and travel date and time (in the next 48 hours).

Based on the above inputs, the backend engine will take the user data, run the data points against our model, and return accident prone sites with the accident probability



Zoom-In view of the predicted probability



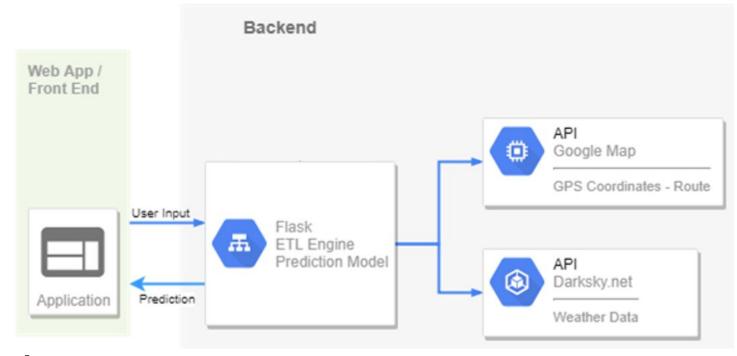
User Friendliness 10 responses

Integrating the front and back end

Front end: The front end will present a clean and simple map to collect user inputs

Back end: The web application was built using Flask, a Python-based server-side language. For the Interactive maps, the backend engine will do the following based on user input:

- Call Google Map API to return a proposed route with a set of GPS coordinates along the route
- Call *Darksky.net API* for weather forecast for the chosen date, time and **GPS** coordinates
- Feed all predictors from both API into the prediction model and return a probability of traffic accidents occurring along the route.

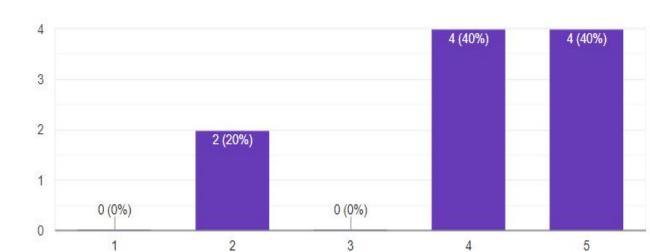


Evaluation

A total of ten participants evaluated our RTA prediction via a survey. Participants are asked to compare our app with Google Maps with real time traffic information. Most respondents found our application:

- user friendly
- more useful in preventing accidents (as compared to Google Maps) Do you think this app is more useful in preventing traffic accidents in

London as compared to Google Maps (https://maps.google.com)?



References:

Fancello et al. (2018) An accident prediction model for urban road networks, Journal of Transportation Safety & Security, 10: 387-405. Sager (2016) Estimating the effect of air pollution on road safety using atmospheric temperature. GRI Working Papers 251. Sun et al. (2014) Crash risk analysis for Shanghai urban expressways: Use of Support Vector Machine Models for Real-Time Prediction of Crash Risk on Urban Expressways, Transportation Research Record: Journal of the Transportation Research Board, 2432: 91-98. Wang et al. (2011) Predicting accident frequency at their severity levels and its application in site ranking using a two-stage mixed multivariate model, Accident Analysis & Prevention, 43:1979-1990.

Yuan et al. (2017) Predicting Traffic Accidents Through Heterogeneous Urban Data: A Case Study. PLoS ONE 13(8): e0201890.

