Estimating Traffic Crash Counts
Using Crowdsourced Data

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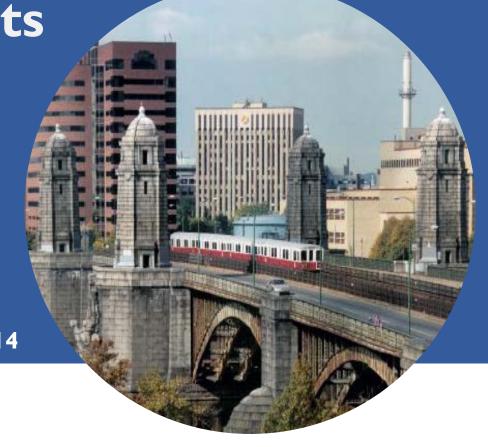
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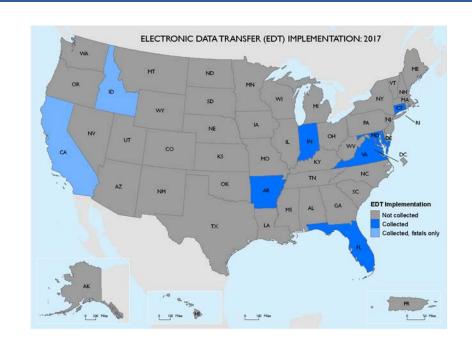
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Challenge: Tracking crashes in near real-time

- Crash data are typically available for certain crashes, after several months
- EDT (Electronic Data Transfer) of police accident reports available nightly for nine states
- Waze incident data available where user reported, all 50 states, every 2 minutes
- Waze and EDT could provide near-real time, granular estimates of crashes to inform safety policy and operations





Safety Data Initiative: Waze Pilot Project Overview

Objectives

 Use crowdsourced data insights to improve transportation safety

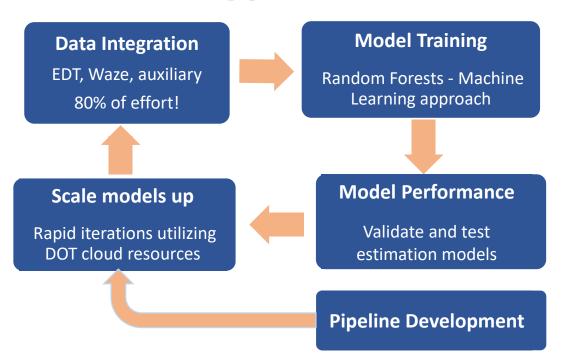
Questions

- Can we integrate DOT data resources at large scales?
- Do Waze data support vision of a rapid crash indictor?

Vision

Rapid crash trend monitoring tool

Approach



Analysis: Challenges and Solutions

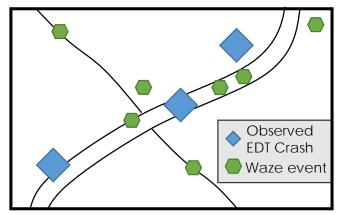
Challenges

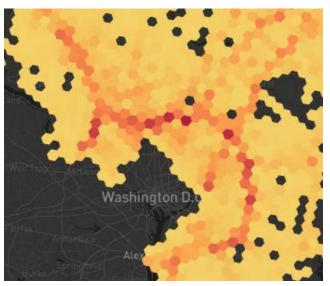
- Waze and EDT coordinates do not all align with FHWA road network
- How do we associate Waze events and EDT reports?
- Need to define zeros (time and places with no accidents)

Solutions

- Spatial aggregation of data to hexagonal grids (1-mile area)
- Match Waze to EDT on user-selected buffers in space and time
- Define zeros as grid cells and time periods with 1 or more nonaccident Waze events but no EDT reports

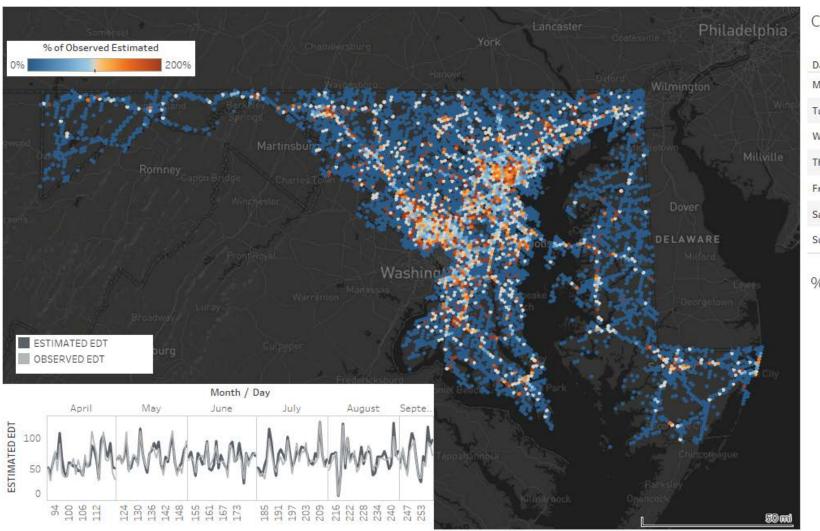
Observed data





Model Performance (April-Sept 2017 in MD)

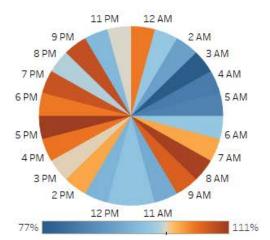
Model estimates highly accurate overall; miss some precise patterns



Crashes by Day

Day Of Week	ESTIMATED EDT	OBSERVED EDT	PRCT OBSERVED
Monday	1,089	1,099	99.09%
Tuesday	1,623	1,602	101.31%
Wednesday	1,788	1,709	104.62%
Thursday	1,768	1,694	104.37%
Friday	1,922	1,840	104.46%
Saturday	1,945	1,869	104.07%
Sunday	1,390	1,413	98.37%

% Observed Estimated by Hour



Results – what have we learned?

Can we integrate DOT data resources at large scales?

- YES Our data integration and analysis pipeline can support rapid crash estimates (when/where Waze signal present)
- Successfully integrated transportation data that are not originally intended to track traffic safety

Do Waze data support rapid crash indicator?

- **YES** With Waze signal, models produce good overall estimates for MD (next test performance for other EDT states)
- Foundation for tool for rapid tracking of traffic safety trajectories













Next Steps

- Model testing and re-training for 4-5 EDT states
- Partnerships with state or local DOTs to identify use cases
- Cross-state Waze data assessment
 & dashboard
- Applications of segment-based models

Potential Applications

Rapid crash trend monitoring tool

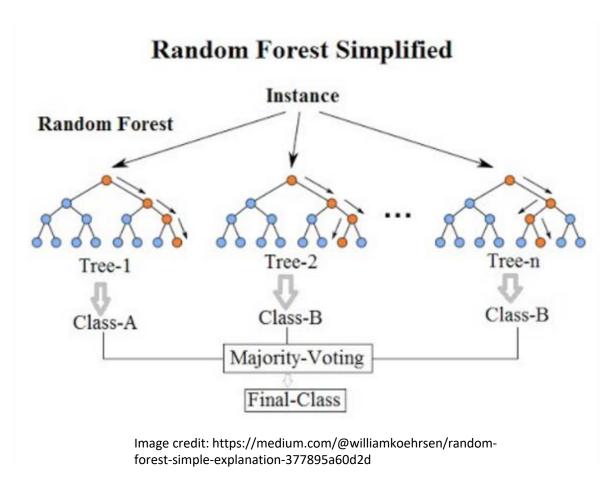
- Flag anomalies
- Short-term intervention assessment
- Cross-state comparisons
- Effectiveness models
- Incident Duration
- Clearance Times
- Secondary Crashes

Additional Slides

Statistical Approach: Supervised Classification

Random Forests

- Machine learning approach which minimizes overfitting
- Trained models on 70% of data using EDT reports as our labeled "ground-truth"
- Tested model performance using 30% of data to compare estimated EDT crashes with observed EDT crashes
- Rigorously trained and tested data feature combinations (50+ models)
- Best crash estimation models minimize False
 Positives and False Negatives



Waze

- JSON files of events every 2 min
- Ingested in data lake

Secure Data Commons

- Curated to S3 and Redshift
- Derived to monthly, gridded data
- Combined with EDT and auxiliary data

ATA Platform



- Estimation of EDT-level crash events using random forests
- Output model results to ATA S3 and local

Output

 Tabular and graphical outputs (ArcMap, Tableau)





Amazon Web Services platform

- Redshift database
- S3 buckets
- RStudio + Jupyter
- GitHub integration

Amazon Web Services platform

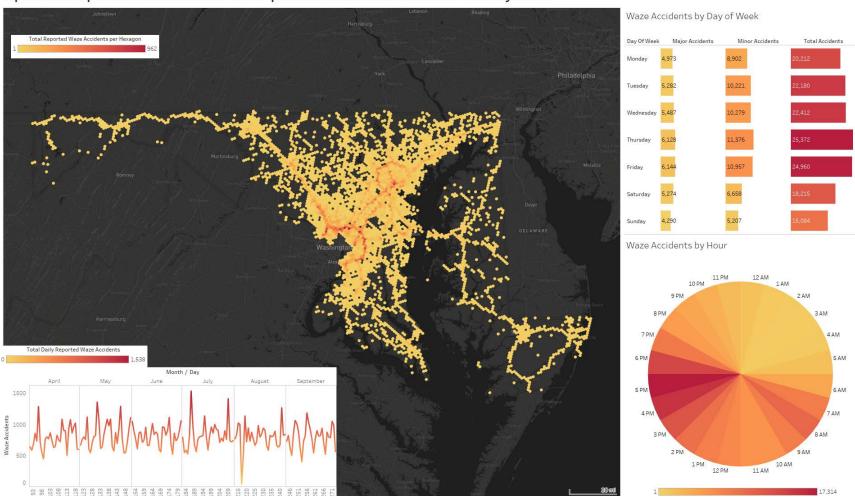
- •S3 buckets
- RStudio + Jupyter
- GitHub integration
- Athena

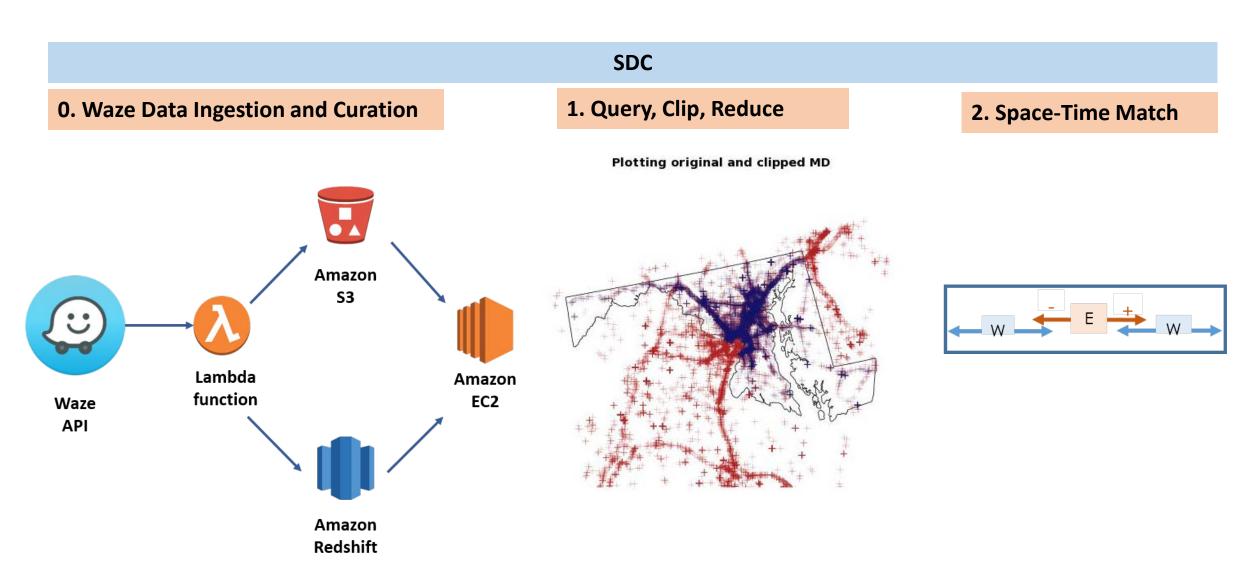


Waze Data: Distribution in Space and Time

Six months of geolocated Waze data for Maryland (April - September, 2017)

Spatiotemporal Distribution of Reported Waze Accidents in Maryland

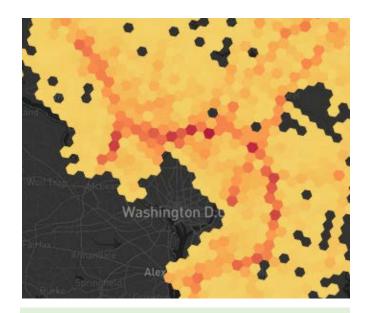




SDC

3. Grid and Urban Area Overlay

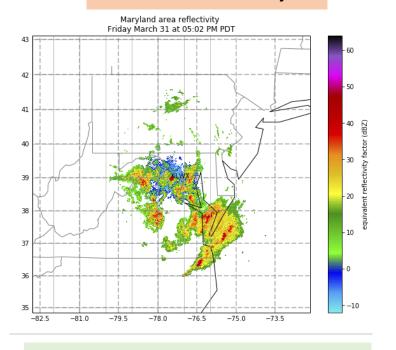
4. Grid Aggregation



Adding:

- Urban Areas
- Hexagonal grid tessellations

5. Weather Overlay



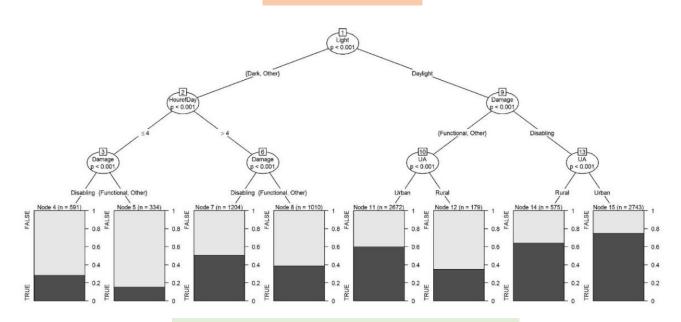
Adding:

Raster weather reflectivity

ATA

ATA + Local

6. Modeling

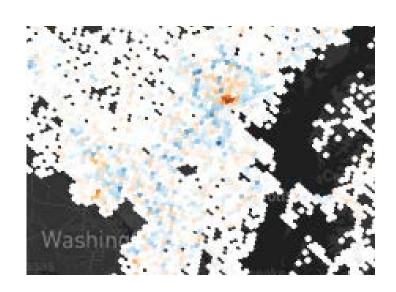


Adding:

FARS

- AADT
- HPMS road class LEHD

7. Visualization and Reporting



Evaluating Model Performance

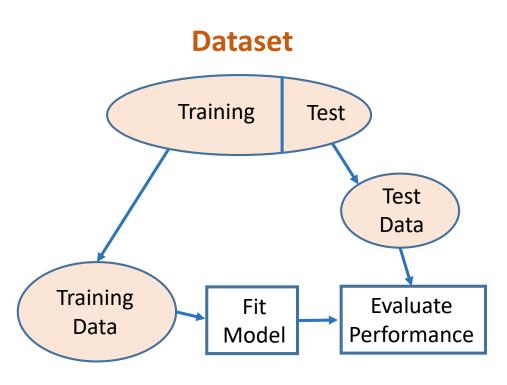
Divide data into training and testing subsets

- Training data: Select 70% of observations (random by rows, whole days, or whole weeks)
- Test data: Remaining 30% of observations

Training: fit model parameters with a large set of known EDT crashes, associated Waze events and other predictors

Testing: apply fitted model parameters to a new set of Waze events and other predictors to generate estimated EDT crashes

Compare estimated EDT crashes to observed EDT crashes in the test data set to evaluate model performance

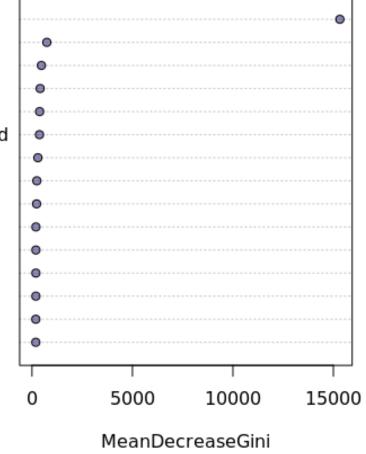


Variable Importance: Waze Accidents (April-Sept)

Mean decrease in Gini impurity:

- Variable is useful in separating a node of mixed classes (both 0 and 1 EDT crashes, in our case) into two nodes with pure classes (all 0 or all 1 EDT crashes).
- Across all nodes in all the trees, how much does this variable decrease node impurities, averaged over all trees?

nWazeAccident nWazeJam medLastRepRate nWazeRT6 nWazeRT3 nWazeWeatherOrHazard medLastConf medMagVar MEAN AADT DayOfWeek nWazeRT7 SUM AADT medLastReliab SUM miles nMagVar240to360



Model 30 Variable Importance

Waze Data: Jams and Crash Sequence Analysis

