Highlights

Modeling the Need for an Ambulance based on Automated Crash Reports from Cell Phones

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- Supports transferability and benchmarking of different approaches on a public large-scale dataset. We have attached the code we used to perform the analysis on the Crash Report Sampling System.
- Novel Application motivated by Emerging Technology: Machine Learning Classification Models for Dispatching Ambulances based on Automated Crash Reports
- New Use of Dataset: Used Crash Report Sampling System (CRSS), which has imputed missing values for some features, but not all of the ones we wanted to use. For the first time we have seen, we used the software the CRSS authors use for multiple imputation (IVEware) to impute missing values in more features.
- Explicit Incorporation of Imbalanced Costs
- Perennial Machine Learning Challenge: Imbalanced Datasets

Modeling the Need for an Ambulance based on Automated Crash Reports from Cell Phones

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ARTICLE INFO

Keywords:
Automated crash notification
Ambulance dispatch
Emergency medical services
Machine learning
Imbalanced Cost
Imbalanced Data
Imputation

ABSTRACT

New Google Pixel phones can automatically notify an emergency dispatcher if the phone detects the deceleration profile of a vehicular crash. Most crash notifications come from an eyewitness who can say whether an ambulance is needed, but the automated notification from the cell phone cannot provide that information directly. Should the dispatcher immediately send an ambulance before receiving an eyewitness report? There are three options: Always, Wait, and Sometimes. The “Always” option refers to sending an ambulance to every automatically reported crash, even though most of them will not be needed. In the “Wait” option, the dispatcher sends police, but always waits for a call from an eyewitness (perhaps the police) before sending an ambulance. In the “Sometimes” option, the dispatcher relies on a machine learning recommendation system to decide whether to immediately dispatch an ambulance, reserving the option to send one later based on an eyewitness report.

This paper explores one option for building a machine learning (ML) model for making a recommendation in the “Sometimes” option. Our goal is to build a model that returns, for each feature vector (crash report, sample), a probability p that the person needs an ambulance. Then we choose a threshold θ such that we immediately send ambulances to those automated crash reports with $p > \theta$, and wait for eyewitness confirmation for those reports with $p < \theta$. In an actual implementation, the choice of θ is political, not technical, so we consider and interpret several options.

Once a threshold has been chosen, the costs of the false positives (FP) and false negatives (FN) in dispatching ambulances are very different. The cost of sending an ambulance when one is not needed (FP) is measured in dollars, but the cost of not promptly sending an ambulance when one is needed (FN) is measured in lives. Choosing such a tradeoff threshold is ethically problematic, but governments implicitly choose such a tradeoff when they set budgets for emergency services.

We consider and interpret several options for θ, some of which consider a relationship between the total number of FP and FN up to that value of p, and others consider the marginal relationship around that value of p. Once the threshold criteria are chosen, the problem turns to choosing and tuning a model that best satisfies the tradeoff, saving both money and lives.

We show that the quality of the model depends highly on the input data available, and we considered three levels of data availability. The “Easy” level includes time of day and weather, data the emergency dispatcher has before the notification. The “Medium” level adds the age and sex of the cell phone user and information about the location. The “Hard” level adds information about the vehicle likely to be driven by the cell phone user and detailed and temporal information about the location, like lighting conditions and whether it is currently a work zone.

We used the data of the Crash Report Sampling System (CRSS) to validate our approach. We have applied new methods (for this dataset in the literature) to handle missing data, and we have investigated several methods for handling the data imbalance. To promote discussion and future research, we have included all of the code we used in our analysis.

1. Introduction

1.1. Outline

- Dataset
    - CRSS

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ORCID(s):

        * 2016-2020, 2021
        * Over-represents more serious crashes
    - Feature Selection and Engineering
    - Discretization
    - Imputing Missing Values

- Imbalanced Data
    - Can't use SMOTE
    - Class Weights
    - Focal Loss
    - Bagging and Boosting Methods
    - Moving the Discrimination Threshold

- Threshold Options
    - Choose the precision that is politically acceptable
    - Total Precision, including Prior Probability equals Posterior Probability
    - Marginal Precision

- Results and Conclusions

2. Literature Review

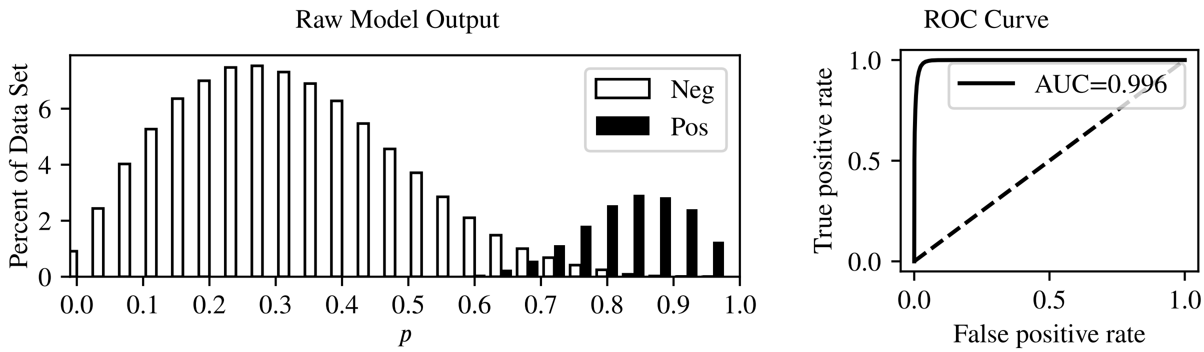
3. Dataset

4. Methods

4.1. Analysis of Results

We would like results like in the graphs below, where the machine learning (ML) algorithm nearly perfectly separates the two classes. A ML algorithm assigns to each sample (feature vector, crash person) a probability that the person needs an ambulance. The histogram shows the percentage of the dataset in each range of p, showing the percentages for the negative class ("Does not need an ambulance") and the positive class ("Needs an ambulance").

On the right, the Receiver Operating Characteristic (ROC) curve, and particularly the area under the curve (AUC), is a metric for how well the model separates the two classes, with $AUC = 1.0$ being perfect and $AUC = 0.5$ (the dashed line) being just random assignment with no insight. Having an AUC of 0.996 is amazing.



Unfortunately, our test results do not look quite that nice. They do not separate the two classes as well, and often they are clustered to one side or in the middle.

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BRFC_Hard_Tomek_0_alpha_0_5_v1_Test
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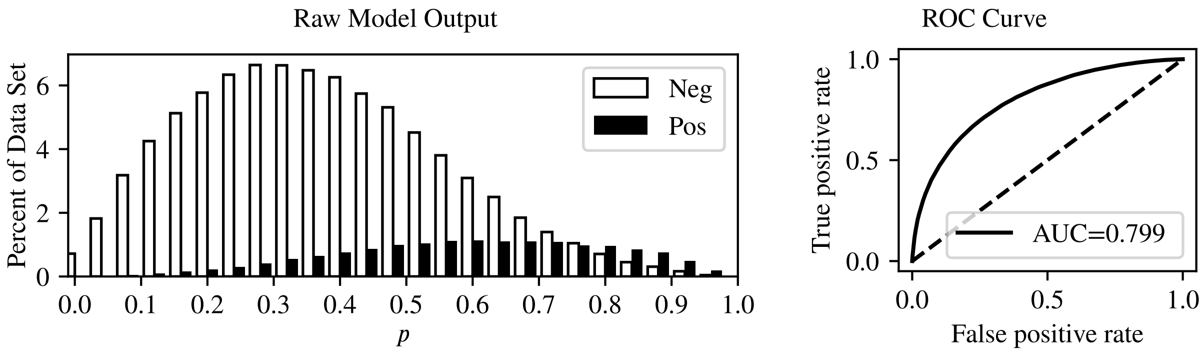
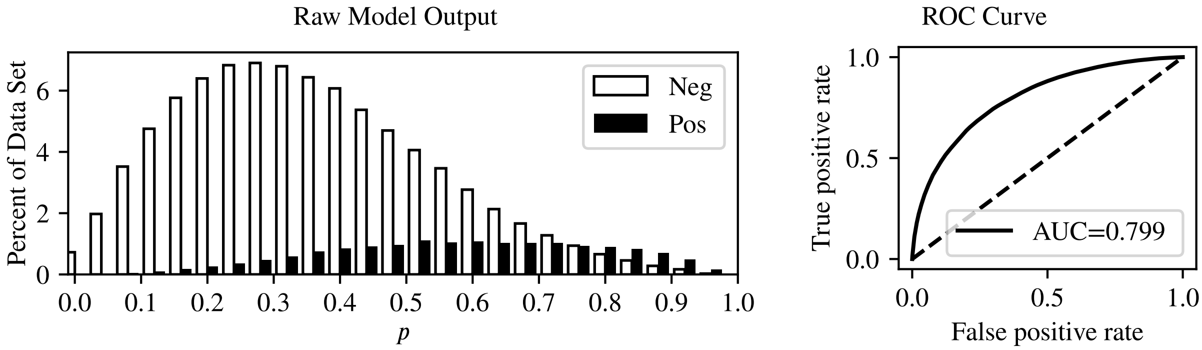


`BRFC_Hard_Tomek_0_alpha_balanced_v1_Test`



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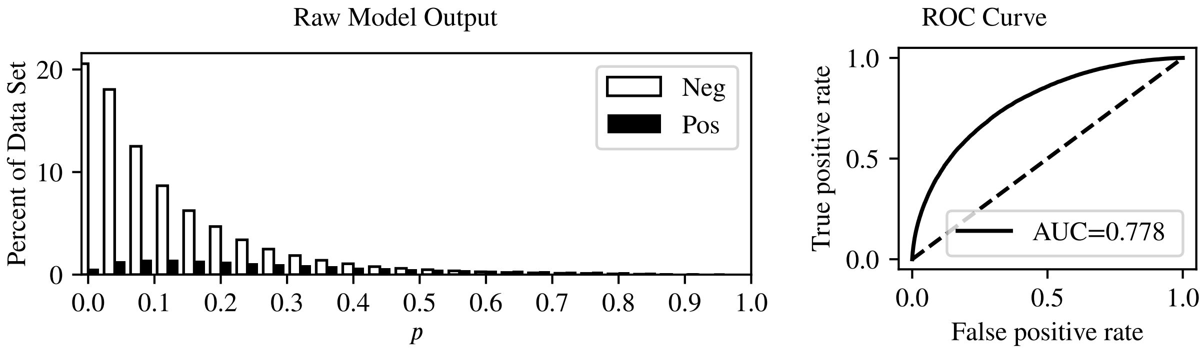

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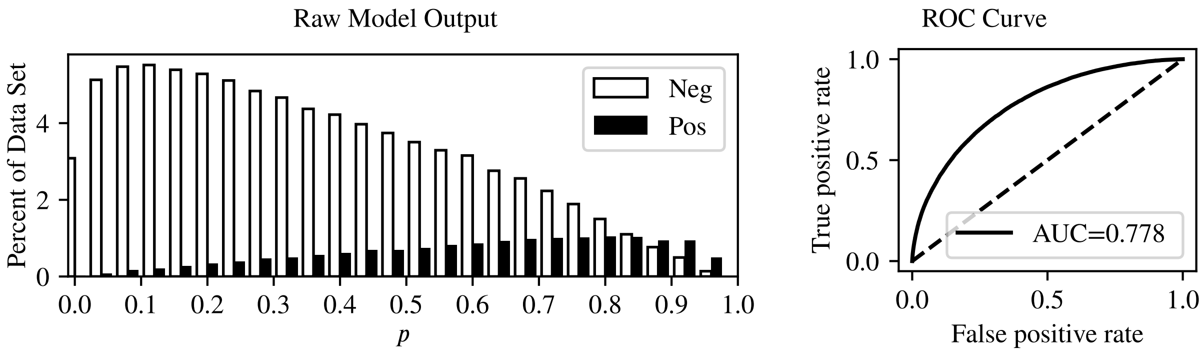

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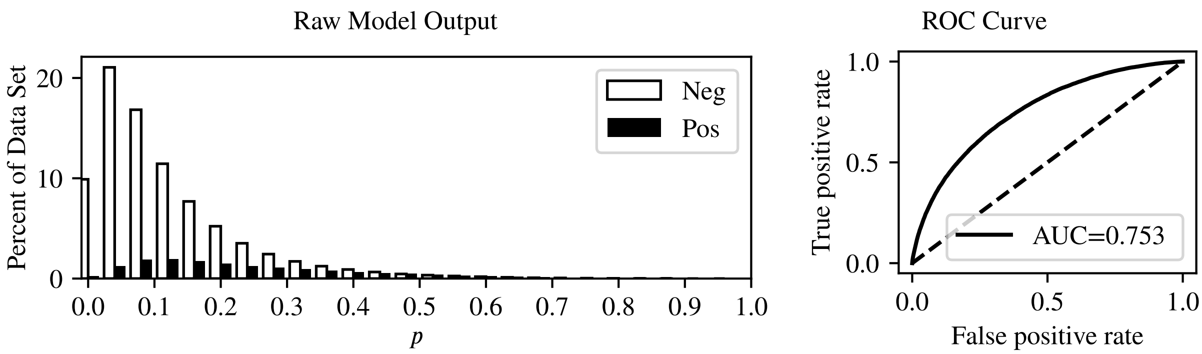

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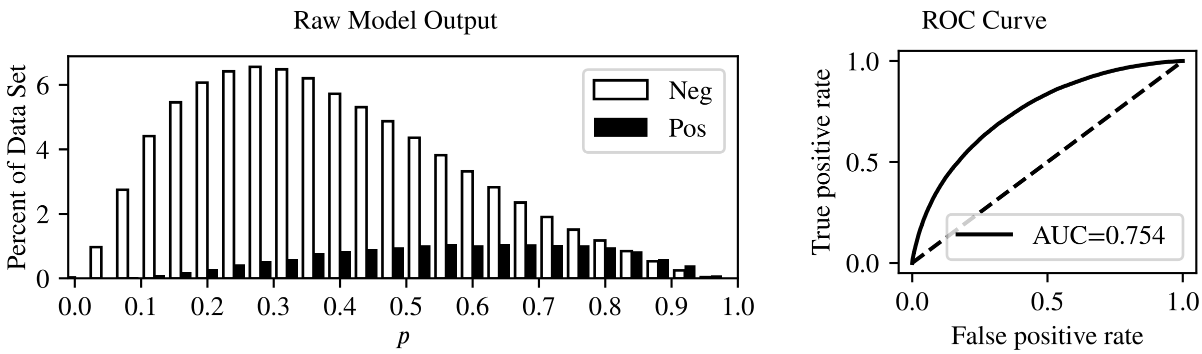

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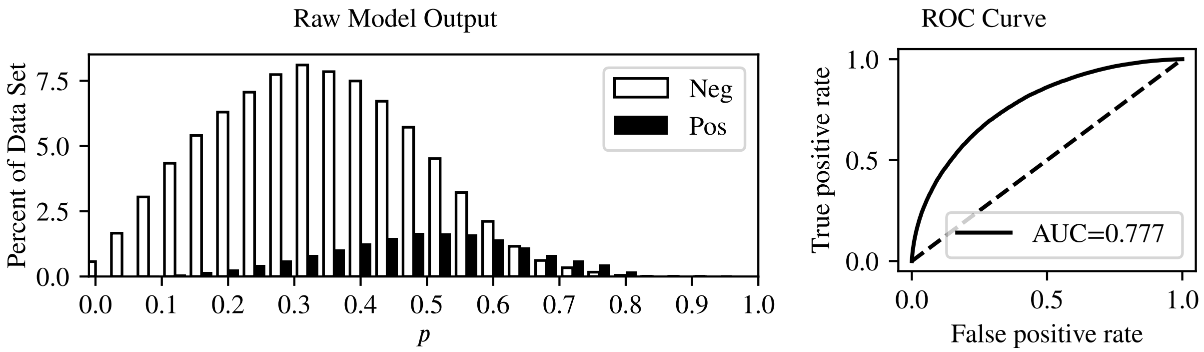

5. Results

6. Conclusions

7. Discussion

8. Future Work

9. To Do, Notes to Self

Funding Statement

Conflict of Interest

The authors have no relevant financial or non-financial interests to disclose.

Acknowledgements

[STUDENT] contributed to this work in the [FUNDED PROGRAM]

Data Availability

The CRSS data is publicly available at
`https://www.nhtsa.gov/crash-data-systems/crash-report-sampling-system`

10.

CRediT authorship contribution statement

First Author: Conceptualization, Investigation, Writing - original draft, Visualization. **Second Author:** Supervision, Methodology, Writing - review and editing. **Third Author:** Investigation, Methodology. **Fourth Author:** Data curation, Writing - review and editing.

References