

Highlights

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

First Author, Second Author, Third Author, Fourth Author

- 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.
- Perennial Machine Learning Challenge: Imbalanced Datasets.

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

First Author^{a,b}, Second Author^a, Third Author^{a,c} and Fourth Author^c

^aSchool, University,

^bOther School,

^cOther Department, University,

ARTICLE INFO

Keywords:

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

ABSTRACT

New Google Pixel phones can automatically notify police if the phone detects the deceleration profile of a crash. From the data available from such an automatic notification, can we build a machine-learning model that will recommend whether police should immediately, perhaps automatically, dispatch an ambulance? If the injuries are serious, time to medical care is critical, but few crashes result in serious injuries, and ambulances are in limited supply and expensive. Such a model will not be perfect, with many false positives (sending an ambulance when one is not needed) and some false negatives (not sending an ambulance when one is needed), but better than random. How much better depends on several things that we will investigate.

A key idea underlying this analysis is that the costs of the false positives and false negatives are very different. The cost of sending an ambulance when one is not needed is measured in dollars, but the cost of not sending an ambulance when one is needed is measured in lives. We propose a way to interpret class weights as the ethical rate of tradeoff.

We will show that the quality of the model depends mostly on what information is available to inform the decision of whether to immediately dispatch an ambulance. Whether a model is “good” is partly a political question, weighing prompt medical care against its high cost, but given a parameter p of how to weigh those costs, we can build that tradeoff into the model.

We used the data of the Crash Report Sampling System (CRSS). This data is freely available online. 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

2. Literature Review


2.1. Apps to Detect Crashes

The idea of using the accelerometer in a cell phone to detect a crash and notify the police goes back to at least 2011 with *WreckWatch*, an app prototype by White, Thompson, Turner, Dougherty and Schmidt (2011). A few years later, Aloul, Zualkernan, Abu-Salma, Al-Ali and Al-Merri (2014) proposed an app that would detect not only a crash but its severity, and send the phone owner’s medical information. In September 2019, Google hinted that it would have crash detection in its Pixel phones soon (Rahman, 2019), and it is now available (Google). In November 2021, the Wall Street Journal announced that Apple was thinking of introducing such an app in its iPhones and Apple watches in 2022 (Winkler (2021)), but as of this writing, such an app had not come out yet. The App Store does have some unverified third-party apps, like those from Sosmart SAP and BlinkApp LLC.

2.2. Imbalanced Data

In building a model to predict, based on records of roadside inspections, traffic violations, and previous crashes, future crashes for trucks, Lack, Berkow and Gao (2021) described the imbalanced data problem well.

Initial models “correctly” classified no-crash versus crash instances 99% of the time, but almost never correctly predicting a crash—a major failure in achieving the goal of this analysis and a common issue in unbalanced datasets.

 FirstAuthor@gmail.com (F. Author)

ORCID(s):

Our work in this paper uses the most straightforward of machine learning (ML) algorithms, the binary classifier. We want to answer, “Should we send an ambulance to this crash,” and are using historical data answering for each crash, “Did we use an ambulance?” We want to build a model that will look at the data we have for a crash and return a prediction. To build it, we will separate our data into a training set and a test set; use the training set to build the model, then evaluate the model on the (unseen during model building) test set.

The model will not be perfect. We want to send ambulances to all of the crashes that need one (True Positive), and not send ambulances to crashes that don’t (True Negative). Sending an ambulance when one is not needed (False Positive) is unnecessarily expensive, but if we don’t send an ambulance when one is needed (False Negative), someone might die unnecessarily.

We can visually organize the success and failures of our binary classification model in a *confusion matrix* (also called *error matrix*, or *contingency table*).

		Prediction	
		N	P
Actual	N	TN	FP
	P	FN	TP

Most machine learning algorithms are designed to maximize *accuracy*, the proportion of classifications that were successful.

$$\text{Accuracy} = \frac{\text{TN} + \text{TP}}{\text{TN} + \text{FP} + \text{FN} + \text{TP}}$$

In many applications, the accuracy is straightforward and useful, but not if the data are imbalanced. In our case, in all of the reported crashes in Louisiana in 2014-2018, there were 645,748 people involved in the crashes, and 55,164 used an ambulance (OCC_MED_TRANS_CD = A), 8.5% of the total.

If we built a model that predicted that none of the crashes required an ambulance, our model would have 91.5% accuracy.

		Prediction	
		N	P
Actual	N	590,584	0
	P	55,164	0

$$\text{Accuracy} = \frac{590,584 + 0}{590,584 + 0 + 55,164 + 0} \approx 0.915$$

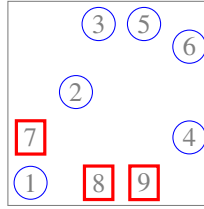
In many applications, 91% accuracy would be good. Why is it different in our context? For two reasons. First, our model is useless because we have entirely misclassified all of the positive samples. Second, accuracy gives the same weight to false positives and false negatives, but in our application, their costs are very different. The cost of a false positive (sending an ambulance when one is not necessary) is measured in money, while the cost of a false negative (not sending an ambulance promptly when one is necessary) is measured in lives. We are willing to trade off sending p number of unnecessary ambulances if it means that we will send one more necessary ambulance. [Choosing the value of p is a question for ethicists and politicians that we will discuss later.]

There are four [citation] categories of methods for building a machine learning model on an imbalanced dataset, and we will use all four in this paper.

- Data-level techniques to artificially balance the dataset
- Modifying the loss function in building the model
- Modifying the model-building algorithm
- Changing the metric in evaluating the model

2.3. Data-Level Techniques for Imbalanced Data

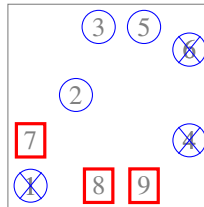
Consider this two-dimensional training dataset, which we will use to illustrate data-level techniques for handling imbalanced datasets. In real problems, of course, the dataset could have a hundred dimensions and a million samples. The six blue circles represent samples (elements) of the majority negative class (“no ambulance”), and the three red squares represent the minority positive class (“ambulance”).



Many algorithms, and variations thereon, have been proposed to balance the two classes before applying a machine learning algorithm to build a model to classify new samples as positive or negative. WARNING: Vast oversimplification ahead. Our goal here is to give the general idea of each method.

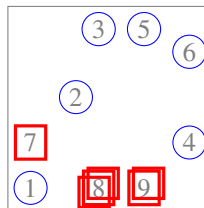
2.3.1. Random Undersampling

Random undersampling balances the two classes by randomly deleting elements of the majority class until the two are balanced. The major drawback of this method is that you throw away information about the majority class. If the majority class is many more times the size of the minority, you lose almost all of the data.



2.3.2. Random Oversampling

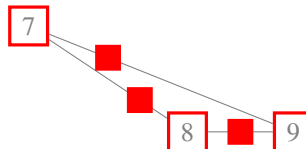
Random oversampling creates duplicates of minority class samples until the sets are balanced. This method has a similar effect to using class weights, introduced below.



2.3.3. Synthetic Minority Sampling Technique (SMOTE)

SMOTE (Chawla, Bowyer, Hall and Kegelmeyer, 2002) is one of the most popular oversampling methods for balancing a dataset with continuous numerical data. It creates new synthetic minority samples “between” original minority samples, not necessarily at the midpoint by choosing a number in $(0, 1)$, multiplying the difference (in each dimension) from point A to B by that constant, and adding it to A .

In the diagram, the solid red squares represent new synthetic samples between pairs of original minority-class samples. SMOTE does not consider the positions of the majority-class samples, only considering the difference in number of nodes to bring the two classes closer to parity.



Michel, Thirion, Grisel, Blondel, Prettenhofer, Weiss, Dubourg, Vanderplas, Passos, Cournapeau, Brucher, Perrot and Duchesnay, 2011)

$$L(y, p) = -(y \log(p) + (1 - y) \log(1 - p))$$

Note that if $y = 0$, then the first term is 0 for any value of p , so only the second term (majority class) is relevant; correspondingly, if $y = 1$, then only the first term is relevant, so a clearer expression might be

$$L(y, p) = -([Loss \text{ if minority class } (y = 1)] + [Loss \text{ if majority class } (y = 0)])$$

Since the logs of $p \in (0, 1)$ will be negative, the negative in front makes the loss positive, and the iterations of the algorithm will seek to minimize it.

2.4.1. Class Weights (Sample Weights, Cost Sensitive Analysis)

Class weights change the error metric, giving more weight to misclassification of minority class samples (King and Zeng, 2001). Giving double weight to misclassified minority class samples would have the same effect as duplicating all of the negative class samples in oversampling. To achieve balance in the contribution of the two classes to the loss function,

$$\text{Let } r = \frac{\text{Total number of samples}}{\text{Number of minority samples}} \quad \text{Let } \alpha = \frac{r}{r + 1} \quad 1 - \alpha = \frac{1}{r + 1}$$

$$L(y, p, \alpha) = -(\alpha y \log(p) + (1 - \alpha)(1 - y) \log(1 - p))$$

2.4.2. Focal Loss

This method is recent, but has appeared in the crash analysis (see Yu, Wang, Zou and Wang (2020) referenced below). Focal loss (Lin, Goyal, Girshick, He and Dollár, 2017) adds another factor to the loss function that gives more weight to samples that are badly misclassified, and less weight to samples that are slightly misclassified.

$$L(y, p, \alpha, \gamma) = -(\alpha y \log(p)(1 - p)^\gamma + (1 - \alpha)(1 - y) \log(1 - p)p^\gamma)$$

The paper by Lin et al. tested values of $\gamma \in [0.0, 5.0]$, and found that $\gamma = 2.0$ gives good balance, but the best value depends on the dataset and the goals. Yu et al's paper using focal loss for real-time crash prediction allowed the γ for minority and majority classes to have different values.

$$L(y, p, \alpha, \gamma_1, \gamma_2) = -(\alpha y \log(p)(1 - p)^{\gamma_1} + (1 - \alpha)(1 - y) \log(1 - p)p^{\gamma_2})$$

2.4.3. Comparison of Loss Functions

The table below compares the three loss functions. For α , we will assume that the minority class is 10% of the dataset, so $r = 10 \rightarrow \alpha = r/(r + 1) = 10/11 \approx 0.9090$. For focal loss, we will use $\gamma = 2$.

Machine learning algorithms use the loss function when comparing two candidate models, only asking which one is less, with no concern for the actual magnitude. For this reason, the choice of base for the logarithm is inconsequential (we arbitrarily choose base 10 for the chart below); also, that the raw focal loss values are each less than the raw class weights, which are each less than the raw log loss, is not relevant, so we have included normalized values for comparing the three loss functions.

Class	y	p	Raw			Normalized		
			Log Loss	Class Weights	Focal Loss	Log Loss	Class Weights	Focal Loss
Minority	1	0.9	0.04576	0.04160	0.00042	0.04560	0.08292	0.00464
	1	0.7	0.15490	0.14082	0.01267	0.15438	0.28069	0.14136
	1	0.5	0.30103	0.27366	0.06842	0.30002	0.54548	0.76309
Majority	0	0.5	0.30103	0.02737	0.00684	0.30002	0.05455	0.07631
	0	0.3	0.15490	0.01408	0.00127	0.15438	0.02807	0.01414
	0	0.1	0.04576	0.00416	0.00004	0.04560	0.00829	0.00046

Note that, with focal loss, most of the total loss comes from the one badly misclassified minority sample, so to minimize the loss, the algorithm needs to do a better job classifying that sample.

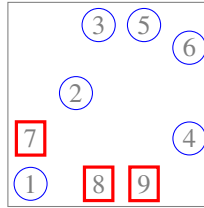
2.5. Algorithm-Level Methods for Imbalanced Data

2.5.1. Bagging

“Bagging” is short for Bootstrapped Aggregating, a variation on random undersampling (Breiman, 1996). In general, bagging takes many random subsets (with replacement) of the samples, run the classifier on each subset, then aggregate the results. In imbalanced data applications, each subset of the samples is all of the n minority samples and n randomly chosen majority samples.

Balanced Random Forest [need citation] is a form of bagging.

In our example, bagging would make a subset of the data with the three minority-class samples (#7, 8, and 9), and three randomly chosen from the majority-class samples, run the classifier; repeat some number of times. Use an ensemble classifier to merge the results.



2.5.2. Boosting

Boosting is an iterative method that runs the classifier multiple times. At the end of each iteration, it determines which samples would be misclassified under the current model. In the next iteration, the classifier gives higher weight to the misclassified samples, improving the model on marginal cases. While boosting is not just for imbalanced data, the challenge in imbalanced data is that the minority class samples get misclassified, so boosting would help. A popular implementation is AdaBoost, introduced by Freund and Schapire (1997).

2.6. Using Different Metrics to Evaluate a Model built on Imbalanced Data

Our goal in building a model is to make an informed guess about a future situation, in our case data from an automated call from the phone of a person involved in a crash. Does the person need an ambulance? We don't know for certain, but using past examples we want a model that will make an informed guess.

To build a model (in supervised learning), we have a set of data (historical data in our case) for which we know the answer to the question, “Did this crash person need an ambulance?” We split the data into two parts, training and test, use the training data to build a model, then evaluate the quality of the model using the test data, for which we now have both the actual answer to the question and the model's educated guess.

When building a model, we test many different models with different algorithms and hyperparameters (user-set parameters, like the γ in Focal Loss) and see which model best solves our problem. To compare two models, we need a metric.

When testing a candidate model, for each sample in the test set, the model returns a probability $Pr \in (0, 1)$ that the sample is a member of the positive (minority) class, in our case, the probability that the crash person needs an

ambulance. We then use a threshold (0.5 by default) to classify the prediction as negative (N, 0) if the probability is less than the threshold, and positive (P, 1) if more. Then we compare the prediction with the actual classification (ground truth), which we can organize into a confusion matrix (truth table).

		Prediction	
		N	P
Actual	N	TN	FP
	P	FN	TP

The most obvious metric is *accuracy*, the proportion of classifications that were successful.

$$\text{Accuracy} = \frac{\text{TN} + \text{TP}}{\text{TN} + \text{FP} + \text{FN} + \text{TP}}$$

Because accuracy gives the same weight to the two classes, it may not be the best metric for imbalanced data sets (because it may overfit the majority class), nor for situations where the cost of a false positive (sending an ambulance when one is not needed) is different from the cost of a false negative (not sending an ambulance when one is needed). Both situations apply to our problem, so we need to consider different metrics, some of which are affected by data imbalance, and some not.

2.6.1. Recall

Recall, or the True Positive Rate (TPR), in our context is, of the calls that actually needed an ambulance, what proportion did the model classify correctly? Increasing recall would save lives. We really want this number to be high, and are willing to trade off other errors to achieve that goal.

$$\text{Recall} = \frac{\text{TP}}{\text{FN} + \text{TP}}$$

Recall only considers the positive (minority) class of the dataset, so it is unaffected by class imbalance.

2.6.2. True Negative Rate

True Negative Rate (TNR, Selectivity, or Specificity), in our context is, of the calls that did not need an ambulance, what proportion did the model classify correctly?

$$\text{TNR} = \frac{\text{TN}}{\text{TN} + \text{FP}}$$

TNR is also not affected by class imbalance because it only considers the classification of the negative (majority) class.

2.6.3. Precision

Precision in our context is, of the ambulances the model would say to send, what proportion were actually needed? Increasing precision would save money.

$$\text{Precision} = \frac{\text{TP}}{\text{FP} + \text{TP}}$$

Note that precision considers elements of both the majority and minority classes, so class imbalance affects the precision, but we can fix that.

2.6.4. Balanced Accuracy and Balanced Precision

Balanced accuracy solves the first problem with accuracy, that it is biased towards the majority class. To balance accuracy, start with the definition of accuracy and scale the majority (negative) class elements (True Negative and False Positive) by the proportions of the positive to negative class, P/N. The results turns out to be the average of the true positive rate and the true negative rate (derivation in the technical paper). That TPR and TNR are unaffected by class imbalance confirms that balanced accuracy is unaffected.

$$\text{Balanced Accuracy} = \frac{\left(TN \cdot \frac{P}{N}\right) + TP}{\left(TN \cdot \frac{P}{N}\right) + \left(FP \cdot \frac{P}{N}\right) + FN + TP} = \frac{TPR + TNR}{2}$$

In the same way, we can make a balanced precision. It can also be written in terms of TPR and TNR, (derivation in the technical paper), or more naturally in terms of TPR and the false positive rate (FPR), the proportion of the negative (minority) class that the model misclassified as positive. In our application, FNR is the proportion of crash persons who did not need an ambulance to whom the model recommends that we should send an ambulance. We have not seen this metric in the literature. We developed it because balanced accuracy is used extensively in the literature, and it seemed natural to want to balance a useful metric (precision) in the same way that accuracy has been balanced.

$$\text{Balanced Precision} = \frac{TP}{TP + \left(FP \cdot \frac{P}{N}\right)} = \frac{TPR + (1 - TNR)}{TPR} = \frac{TPR + FPR}{TPR}$$

2.6.5. F1 and G-Mean

These two popular metrics are each the combination of two other metrics.

F1 is the harmonic mean of Precision and Recall. It is often weighted to emphasize one or the other; if $\alpha = 0.5$, the weighted is the same as the original. We can also substitute Balanced Precision (above) to make a Balanced F1.

$$F1 = \frac{2}{\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}} = \frac{2 \cdot TP}{2 \cdot TP + FP + FN}$$

$$\alpha\text{-weighted F1} = \frac{1}{\frac{\alpha}{\text{Precision}} + \frac{1-\alpha}{\text{Recall}}}$$

$$\text{Balanced F1} = \frac{2}{\frac{1}{\text{Balanced Precision}} + \frac{1}{\text{Recall}}}$$

Gmean is the geometric mean of Precision and Specificity (TNR).

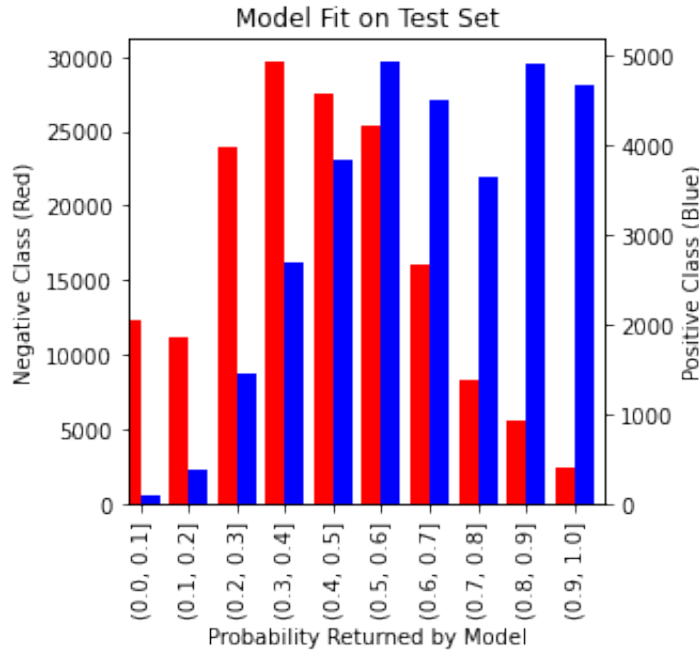
$$\text{Gmean} = \sqrt{\text{Precision} \times \text{Specificity}} = \sqrt{\frac{TP}{TP + FP} \times \frac{TN}{TN + FP}}$$

In this paper we have a binary classification model, but Liu, Lyu, Liu and Cao (2021) adapted class-weighted F1 for classification of multiple classes in a multi-modal recommendation system. That paper has an excellent discussion of why and how they applied the class-weighted F1 metric in post-processing, because the metric is not differentiable.

2.6.6. Over-Predicting the Minority Class

One tests a model by using it to classify the samples in a test subset of the data. For each sample, the model gives a probability $Pr \in (0, 1)$ that the sample belongs to the positive class. Ideally, most of the samples will fall close to the extremes, clearly classified as either positive or negative, indicating that our model is strong and is more likely to correctly classify future samples, but in practice many samples will not be so clearly classified.

The bar graph below illustrates one model classifying the samples of the CRSS dataset into negative (red, ambulance not needed, majority class) and positive (blue, ambulance needed, minority class). The horizontal axes represents the probability $Pr \in (0, 1)$ given by the model that a sample belongs to the class, and the vertical is the number of samples that fall in each probability range.



By default, one uses a threshold $Pr = 0.5$ to assign the samples to the negative (majority, $Pr < 0.5$) or positive (minority, $Pr > 0.5$) classes, but we are free to change that threshold. In the bar graph, all red elements to the left of the threshold are TN, all red elements to the right are FP, all blue elements to the left are FN, and all blue elements to the right are TP. The threshold is a hyperparameter that affects all of the above metrics; for example, decreasing the threshold would shift samples from TN to FP, and from FN to TP. Decreasing the threshold would over-predict the minority class, and increasing it would under-predict.

The chart below gives metrics on that model on the CRSS dataset for different thresholds t . The last column is the marginal tradeoff between unneeded ambulances sent and needed ambulances not sent; for instance, at threshold $p = 0.50$, the difference between $p = 0.45$ and $p = 0.55$ is 5.99 ambulances unnecessarily sent for every needed ambulance not sent. If we (as a society) believe that that cost is too high and we should send fewer ambulances, we should choose a larger threshold value and under-predict the minority class. For the purposes of this paper we have arbitrarily chosen 10 as the number of additional false alarms we are willing to tolerate for each additional ambulance sent when needed, so we could change the threshold to somewhere in $0.3 < t < 0.4$, over-predicting the minority class.

t	TN	FP	FN	TP	TPR	FPR	$\frac{\Delta TPR}{\Delta FPR}$	$\frac{\Delta FP}{\Delta TP}$
0.00	0	162200	0	31083	1.00	1.00	0.02	246.76
0.10	12322	149878	84	30999	1.00	0.92	0.09	58.08
0.20	23556	138644	455	30628	0.99	0.85	0.26	20.33
0.30	47541	114659	1895	29188	0.94	0.71	0.37	14.10
0.40	77254	84946	4590	26493	0.85	0.52	0.60	8.74
0.50	104764	57436	8425	22658	0.73	0.35	0.87	5.99
0.60	130098	32102	13362	17721	0.57	0.20	1.23	4.25
0.70	146094	16106	17860	13223	0.43	0.10	1.77	2.95
0.80	154351	7849	21506	9577	0.31	0.05	3.09	1.69
0.90	159855	2345	26404	4679	0.15	0.01	8.00	0.65
1.00	162200	0	31083	0	0.00	0.00	14.18	0.37

2.6.7. Area Under the ROC Curve [Needs Citations]

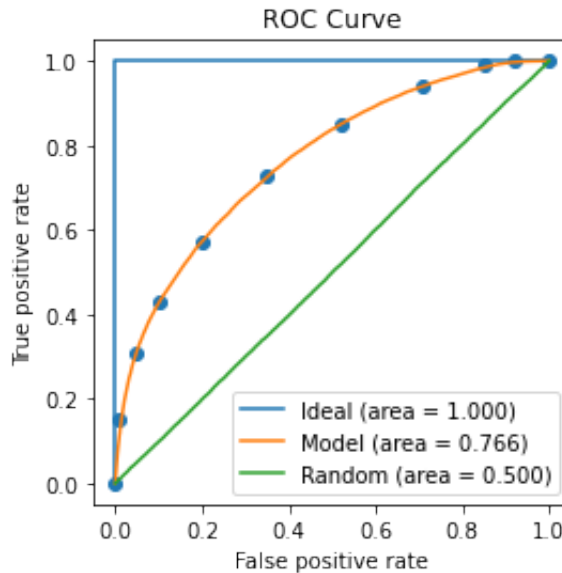
The Receiver Operating Characteristic (ROC) shows how much the positive and negative classes are interleaved. It is a parameterized curve following the probability threshold from $t = 0$ to $t = 1$, and plotting the true positive rate

(TPR) versus the false positive rate (FPR). The orange “Model” curve in the graph below is from the same dataset predictions in the chart above. The eleven points correspond to the (FPR,TPR) coordinates in the chart, going from $t = 0.0$ in the upper right to $t = 1.0$ in the lower left. The next-to-last column in the chart gives the slope of the ROC curve.

If the model gave entirely random results, the bars in the bar chart above would all have the same height (1/20 of the number of elements in the class), and the slope of the ROC curve would be 1, illustrated by the green line, and the area under the curve (AUC) would be 0.5. If our model and dataset were ideal, with all of the negative elements having $Pr = 0.0$ and all of the positive elements having $Pr = 1.0$, the ROC curve would be the blue Γ , with area under the curve of 1.0. In practice, the area under the curve is between 0.5 and 1.0.

The area under the ROC curve is useful for comparing different models on the same dataset. A higher area generally means that the model more clearly separates the two classes, and is more likely to correctly classify elements of a different (but related) set of samples.

Because both TPR and FPR are unaffected by class imbalance, the ROC curve is as well.



2.7. Imbalanced Data in Crash Analysis

Imbalanced data is a frequent concern in crash analysis. In crash prediction, “non-crash” samples are much more numerous than “crash” samples.

2.7.1. Oversampling

Parsa, Taghipour, Derrible and Mohammadian (2019) used SMOTE to balance the dataset of crashes on Chicago’s Eisenhower expressway. Li, Abdel-Aty and Yuan (2020) used SMOTE to study crashes on urban arterials. Guo, Zhao, Yao, Yan, Su, Bi and Wu (2021) used SMOTE to consider risky driving behavior in crash prediction. Orsini, Gecchele, Rossi and Gastaldi (2021) used SMOTE in building a real-time conflict prediction model. Elamrani Abou Ellassad, Mousannif and Al Moatassime (2020) used SMOTE in studying crash prediction for collision avoidance systems. Morris and Yang (2021) compared three oversampling methods, random over-sampling, SMOTE, and adaptive synthetic sampling, for crash data analysis. Yahaya, Guo, Fan, Bashir, Fan, Xu and Jiang (2021a) compared three oversampling methods studying contributing factors in fatal crashes in Ghana, and the same group applied the majority weighted minority oversampling (MWMOTE) method to study multiple fatal injury crashes (Yahaya, Guo, Jiang, Bashir, Matara and Xu, 2021b).

2.7.2. Multiple Techniques

Schlögl, Stütz, Laaha and Melcher (2019) used SMOTE and maximum dissimilarity undersampling to balance an Australian dataset to build a model to predict crashes, while in a later paper Schögl used a balanced bagging approach (Schlögl, 2020). Chen, Shi, Wong and Yu (2020) used SMOTE and Tomek’s links in studying crash

potential in lane-changing behavior. Peng, Li, Wang, Gao and Yu (2020) used undersampling, SMOTE, cost-sensitive algorithms, and boosting. Li, Li, Yuan, Lu and Abdel-Aty (2021) used the proximity weighted synthetic oversampling technique (ProWSyn) method to build a traffic violation prediction model. Chen, Lu, Fu, Sze and Ding (2022a) compared Synthetic Minority Over-Sampling Technique for panel data (SMOTE-P) with Random Under-sampling of the Majority Class (RUMC) technique, Cluster-Based Under-Sampling (CBUS), and mixed resampling to identify explanatory factors that affect the crash risk of buses in Hong Kong. Chen et al. (2020) used ENN-SMOTE-Tomek Link (EST) in estimating crash risk in lane changing.

2.7.3. *Image (or Image-like) Data*

Formosa, Quddus, Ison, Abdel-Aty and Yuan (2020) used Deep Neural Network (DNN) models with a Mean Squared False Error loss function to analyze images from front-facing cameras in cars on a UK roadway to predict crashes. Lin, Li, Jing, Ran and Sun (2020) used Generative Adversarial Networks (GAN) to overcome data imbalance for their incident detection model. Islam, Abdel-Aty, Cai and Yuan (2021) found that a variational autoencoder was more useful than SMOTE, ADASYN, and GAN for generating minority samples to balance crash and non-crash events. Basso, Pezoa, Varas and Villalobos (2021) used Deep Convolutional Generative Adversarial Networks technique with random undersampling to use image and image-like data to build an accident-prediction model for a section of highway in Chile. Man, Quddus and Theofilatos (2022) used Wasserstein GAN (WGAN) and random undersampling to study the transferability of a model built on one dataset to other datasets. Cai, Abdel-Aty, Yuan, Lee and Wu (2020) compared deep convolutional generative adversarial network (DCGAN) with SMOTE and random undersampling to study the effects of proactive traffic safety management strategies such as variable speed limits and dynamic message signs.

2.7.4. *Other*

Lack et al. (2021) used bagging in predicting crashes for trucks and finding ways to improve truck safety. Haule, Ali, Alluri and Sando (2021) used boosting in studying the effects of ramp metering on traffic safety. Yu et al. (2020) implemented the new focal loss technique in real-time crash prediction. Shi, Wong, Li, Palanisamy and Chai (2019) used undersampling to analyze factors predicting risky and safe driving. Zhu and Wan (2021) used cost-sensitive semi-supervised logistic regression (CS3LR) for hit-and-run analysis.

2.7.5. *Imbalanced Data in Other Transportation Areas*

Mohammadi, He, Ghofrani, Pathak and Aref (2019) used the Adaptive Synthetic Sampling Approach (ADASYN) on a dataset of foot-by-foot track geometry and tonnage to identify the factors that predict rail defects. Shi and Zhang (2021) developed a hierarchical over-sampling bagging method based on Grey Wolf Optimizer (GWO) algorithm and Synthetic Minority Over-sampling Technique (SMOTE) to study lane changing for autonomous vehicles. The data was severely imbalanced because lane changing is rare compared with lane keeping. Khan, Ma, Chung and Wen (2021) used SMOTE and Tomek links and “average balanced recall accuracies” for flight delay prediction. Chen, Liu, Wang and Yamamoto (2022b) used bagging for ride-hailing demand prediction.

In crash severity, most reported crashes are just property damage only (PDO), and many PDO crashes aren't even reported. Other aspects of transportation also have imbalanced data, including

- Jiang, Yuen and Lee (2020) used similar data and addressed the challenges we'll have with it.
- Elamrani Abou El Assad et al. (2020) works with several imbalanced methods. Use this paper as a model.

2.7.6. *Ambulances*

- Park and Oh (2019) has a full-page table categorizing studies of ambulance location, relocation, and dispatching using different optimization methods.

3. *Methods*

We used the Crash Report Sampling System (CRSS) NHTSA (2016-2020) data to train and test our model. After preparing the data, we built a variety of models with different combinations of techniques for handling imbalanced data, model types, loss functions, and sets of features, with the overall goal of finding an optimal combination of methods to give the most useful model.

3.1. Dataset Overview

The Crash Report Sampling System (CRSS) (NHTSA, 2016-2020) is an annually published anonymized sample of crash reports in the US, produced by the National Center for Statistics and Analysis (NCSA) of the National Highway Transportation Safety Administration (NHTSA) of the US Department of Transportation (DOT). CRSS replaced the National Automotive Sampling System (NASS) General Estimates System (GES) in 2016. This paper uses 2016-2020 data; the 2021 data is due out in spring 2023.

For each year, the CRSS data comes in three main files, the first with a row for each crash (`Accident.csv`), the second with a row for each vehicle involved in the crash (`Vehicle.csv`), and the third with a row for each person involved in the crash (`Person.csv`). Each year also has (depending on the year) about twenty other files with more detail, which we did not investigate. Putting the five years together, the `Accident` file has 51 features with 259,077 samples, the `Vehicle` has 97 features with 457,314 samples, and the `Person` has 67 features with 644,274 samples. Some features were added or discontinued during these five years.

All of the data is discrete or categorical. Some of the features have ordered data (year, month, hour), but some of them are unordered (make of vehicle). Most features have missing data with a value (like 9 or 99) to signify “missing.” Some features had their missing values imputed (in a separate feature, so we know which samples had the value missing).

Accompanying the CRSS data are a very useful Analytical Users Manual (National Center for Statistics and Analysis, 2022) and a report on how (and why) they imputed missing values in some but not all features. (Herbert, 2019)

3.2. Preparing the Data

To prepare the data for building a model we have two challenges. First, the data has missing values, and we need to choose an approach to handling them. Second, some features have too many unique values for effective model building, and we need to group (bin, discretize) them into larger categories.

To handle the missing values, we have three options, to throw out the samples with missing values in the features we are using to build the model (around 30% of the samples), to treat “missing” as its own value in each feature, or to use some statistical or machine learning method to impute missing values. We chose to impute missing values.

To impute missing values on some features, the CRSS authors used IVEware: Imputation and Variance Software, which uses multivariate sequential regression, and the CRSS imputation report gives the values for the hyperparameters they used. (Herbert, 2019) Of the forty-three features we want to use for our most robust model, only eight were imputed in CRSS; the other thirty-five features have one or more values signifying “Missing.”

Why did the CRSS authors not impute missing values in all of the features? For some features it is the nature of the data. In other fields, like VIN (Vehicle Identification Number), if that data is missing from the report, there is no way to recover, or even guess at, that information using other data in the sample. On the bureaucratic form that is a police crash report, the police jurisdiction is usually printed on the form, and the date is one of the first fields that the reporting officer understands is vital. No CRSS samples have the month or day of week missing; however, CRSS does impute `DAY_WEEK` as `WKDY_IM`, with exactly the same values. The fuller logic for which fields get imputed is partly the nature of the data but also backwards historical compatibility with CRSS’s predecessor databases going back to 1982. See the CRSS technical report on imputation for fuller details. (Herbert, 2019)

An interesting question arises, of whether the order of operations matters. Does it make a difference whether we impute first, then bin, or bin first, then impute? We tested by removing all samples with a missing value, deleting 15% of known values, running impute/bin and bin/impute, then comparing the success rates of the imputations. We found that the difference between the two methods is negligible, that the randomness caused as much difference as the order of operations. For full details see the attached code, `CRSS_11_09_22_Bin_Impute.ipynb`. We decided to bin then impute, because IVEware could not handle categorical features with more than about forty unique values, so we had to bin some of the features before imputing anyway.

We compared three methods for imputing missing values. The first method was to impute to mode: Assign to each missing value the most common value in that feature. This method is not only easy but widely used. The second method was IVEware, using the same hyperparameters as the CRSS authors used. The third method was Random Forest Classifier, using the mode as the starting guess. Random Forest and IVEware were both better than Mode, and Random Forest was arguably better than IVEware, but not by much and not in all features. Both Random Forest and IVEware correctly imputed about 77% of missing values. For full details, see the attached code, `CRSS_05_Impute_Random_Forest_12_22_22`.

To bin the values in each feature into fewer categories, for some features the best binning was straightforward. The HOSPITAL feature in the Person dataset, which we made the target variable for our models, has nine values, one signifying that the person did not go to the hospital, six telling how the person got to the hospital (by air, by law enforcement, by emergency medical services but unknown mode, by EMS ground, transported by other method, or other), and two values signifying that the report didn't say whether the person went to the hospital. For our purposes, it does not matter how the person got to the hospital, only that the person went. We reduced the nine values to three: Hospital True, Hospital False, and Hospital Unknown. Many features were this straightforward.

Other features were like MAKE, which has sixty-seven unique values with no clear order. The chart below shows the major manufacturers. To avoid the curse of dimensionality when we change the bins to dummy variables, we ideally want to put the sixty-seven values into five to ten bins, but does Toyota go in the same bin with Ford or Hyundai? We imposed an ordering on the set, based on how likely someone in that make of car was to go to the hospital. We then put them into nine bins, and one bin for "Unknown Make." we divided the nine bins first along significant changes in the percent hospitalized, like the one between the motorcycles and the passenger cars and the one between the cars and the heavy trucks, and then into approximately even numbers of persons in each group when there was no clear line.

Note that "Bluebird" here is a school bus, not the Nissan Bluebird. Also, some of the makes, like Volvo and Mercedes-Benz, include both passenger cars and heavy trucks.

The feature MAK_MOD, make and model, has 1200 categories that we similarly mapped into five bins of approximately equal number of persons by their hospitalization rates.

For full details on the binning, see the code, CRSS_04_Discretize_11_19_22.

Ambulance Dispatch

MAKE	Percent of Persons	Percent of those Persons Hospitalized
Yamaha	0.33	63.16
Harley-Davidson	0.82	61.86
Kawasaki	0.26	60.61
Suzuki	0.44	45.11
Other Make	0.63	30.46
Mitsubishi	0.78	16.66
Pontiac	0.87	16.56
Mercury	0.54	16.29
Buick / Opel	1.36	16.07
Saturn	0.50	15.89
Honda	8.85	15.81
KIA	2.95	15.46
Nissan/Datsun	7.71	15.23
Chrysler	1.95	15.07
Fiat	0.06	15.00
Hyundai	3.67	14.87
Chevrolet	11.93	14.25
Lincoln	0.56	13.99
BMW	1.21	13.69
Toyota	11.09	13.34
Volkswagen	1.42	13.29
Ford	12.67	13.16
Cadillac	0.87	12.95
Jeep	3.03	12.76
Mazda	1.4	12.70
Infiniti	0.82	12.66
Dodge	5.56	12.44
Mercedes-Benz	1.23	12.39
Acura	0.94	12.35
GMC	2.49	11.95
Lexus	1.34	11.58
Subaru	1.22	10.58
Audi	0.48	9.59
Volvo	0.57	9.02
Bluebird	0.05	7.88
Thomas Built	0.02	7.52
Mack	0.17	4.35
International Har- vester/Navistar	0.48	4.06
Freightliner	0.85	4.03
Kenworth	0.26	3.92
Peterbilt	0.31	3.11
Not Reported	0.27	1.20
Unknown Make	2.07	3.24

3.3. Feature Selection

In selecting features from the CRSS dataset, we chose features that could be known or inferred at the time of the crash without an eyewitness. We separated them into three sets in terms of how hard the data would be to get in good quality: Easy, medium, and hard. The easy information is a baseline, the information the police have before they receive the notification, like locality, time of day, and weather. The medium level requires detailed maps to distinguish

between, for example, an intersection and a parking lot, and information from the phone service provider about the primary user of the phone. The hard level would require coordination of private (cell service providers, Apple Google) and public databases (police, government vehicle registries), or correlating several notifications from different phones at about the same time from about the same location to see that they are probably the same crash event.

Location

Easy

Region (4 regions of the US)

Principal Sampling Unit (74 subregions of the US)

Police Jurisdiction (422 jurisdictions)

Urban/Rural

Medium: Requires precise location and maps

Interstate

In intersection (Yes/No)

Type of intersection

Position relative to the road

Position relative to an intersection

Roadway alignment (curve, straight, driveway,...)

Number of lanes in roadway

Roadway grade

Speed limit

Traffic control device (stop lights, stop signs)

Trafficway description (two way, divided, ramp,...)

Medium: Requires up-to-date maps

Work Zone

Hard: Requires very detailed maps

Relation to junction features

Time

Easy

Hour

Weekday/Weekend

Month

Year

Weather

Medium: Requires detailed maps per time of day

Lighting Conditions

Phone User

Medium: Requires identifying phone user

Age

Sex

Medium: Requires storing acceleration data for several minutes

Pedestrian / In moving vehicle

Hard: Requires identifying the vehicle used by phone user

Make of vehicle

Model of vehicle

Age of vehicle

Body type of vehicle

Hard: Requires identify licensing of phone user (driver) or ages from several phones (bus passengers)

School bus

Type of other bus

Emergency vehicle

Correlate Multiple Notifications

Hard

Number of people in vehicles

Number of occupants of particular vehicle

Number of vehicles in motion

Number of parked vehicles

3.4. Feature Engineering

From the features in the dataset, we can create new features that may be relevant, like “Rush Hour,” combining hour with day of week. During rush hour, the number of crashes increases, but their average severity goes down. We drew the lines distinguishing “Rush Hour” from “Not Rush Hour” based, again, on the correlation to hospitalization. Interestingly, the hospitalization rates varied by age, and varied by sex, but varied differently by age within sex. Hospitalization rates for young children are low, perhaps due to child seat requirements, but after young childhood, as age increases, the hospitalization rate increases for both men and women, but younger women have a lower hospitalization rate than men, and older women have a higher rate. We created an AGE_SEX feature.

Crash Person Count			
Age	Female	Male	Total
00-06	12331	12639	24970
07-15	16623	16726	33349
16-18	20158	21622	41780
19-52	175528	219931	395459
53-70	49750	65228	114978
71+	15972	17766	33738
Total	290362	353912	644274

Hospitalization Count			
Age	Female	Male	Total
00-06	1448	1560	3008
07-15	2529	2779	5308
16-18	2900	2998	5898
19-52	28843	33514	62357
53-70	9302	10947	20249
71+	3503	3287	6790
Total	48525	55085	103610

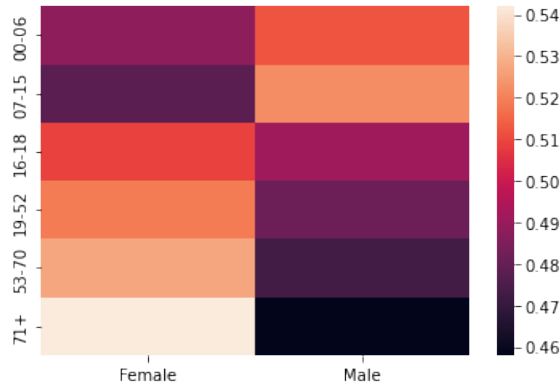
Ambulance Dispatch

Hospitalization Rate

Age	Female	Male	Total
00-06	0.117	0.123	0.240
07-15	0.152	0.166	0.318
16-18	0.144	0.139	0.283
19-52	0.164	0.152	0.316
53-70	0.187	0.168	0.355
71+	0.219	0.185	0.404
Total	0.983	0.933	1.916

Rate Normalized by Row

Age	Female	Male	Total
00-06	0.488	0.512	1.0
07-15	0.478	0.522	1.0
16-18	0.509	0.491	1.0
19-52	0.519	0.481	1.0
53-70	0.527	0.473	1.0
71+	0.542	0.458	1.0
Total	3.063	2.937	6.0



Hospitalization Rate Normalized by Age

For full details see the code `CRSS_05_24_22_Crosstabs`.

3.5. Handling Data Imbalance and Building Models

In the Literature Review section we enumerated many methods for dealing with data imbalance, most of which are relevant to our problem. In the code `CRSS_06_Build_Model_01_15_22.ipynb` we implemented these methods. We tried all of them, individually and in combinations, to see which combinations of methods give the most effective model.

- Ensure that the training and test sets have the same proportion of positive and negative class samples
- Tomek Links, both once and twice
- Balanced Metrics
 - Balanced Accuracy
 - Balanced F1
 - Balanced Precision

- Loss Functions
 - α -weighted Binary Crossentropy
 - Focal Loss
- Model Algorithms
 - Keras Simple Neural Network
 - AdaBoost Classifier
 - Balanced Bagging Classifier
 - Balanced Random Forest Classifier

3.6. Class Weights as Ethical Tradeoff

Many loss functions incorporate a class weight hyperparameter, here given by α . One of its uses is to accommodate class imbalance, described above, where we let $1/r$ be the proportion of samples in the minority class.

$$\text{Let } r = \frac{\text{Total number of samples}}{\text{Number of minority samples}} \quad \text{Let } \alpha = \frac{r}{r+1} \quad 1 - \alpha = \frac{1}{r+1}$$

The loss function for each sample is given by L , and the total loss is the sum of those sample losses, J .

$$L(y, p, \alpha) = -(\alpha y \log(p) + (1 - \alpha)(1 - y) \log(1 - p))$$

$$J(y, p, \alpha) = -\sum_{i=1}^N (\alpha y_i \log(p_i) + (1 - \alpha)(1 - y_i) \log(1 - p_i))$$

Let us recall the confusion matrix, in terms of y_i and p_i . We will use it to switch between binary and continuous versions of the loss functions.

	Do Not Send Ambulance $p_i \leq 0.5$	Send Ambulance $p_i > 0.5$
Ambulance Not Needed $y_i = 0$	TN	FP
Ambulance Needed $y_i = 1$	FN	TP

In the (unweighted) binary cross-entropy loss function,

$$J = -\sum_{i=1}^N y_i \log(p_i) + (1 - y_i) \log(1 - p_i)$$

the y_i are binary, $y_i \in \{0, 1\}$, but the model predictions, p_i , are a probability, $p_i \in (0, 1)$.

If we treat the model predictions as binary, replacing

$$\log(p_i) \rightarrow \begin{cases} 0 & \text{if } p_i \leq 0.5 \\ 1 & \text{if } p_i > 0.5 \end{cases} \quad \text{and} \quad \log(1 - p_i) \rightarrow \begin{cases} 0 & \text{if } 1 - p_i \leq 0.5 \\ 1 & \text{if } 1 - p_i > 0.5 \end{cases}$$

then

$$TP = \sum_{i=1}^N y_i \log(p_i) \quad \text{and} \quad TN = \sum_{i=1}^N (1 - y_i) \log(1 - p_i)$$

and the loss function becomes $J = -(TP + TN)$.

We use the continuous version when building the model, because we want the predictions to be robust, so that when we use the model on unseen data we can be more certain that it will correctly classify new instances. We use

the binary when we evaluate the model on unseen data, because then we only care about whether the model gets the classification right or wrong. The binary is also easier to explain.

If the medical ethicists and politicians decide on a tradeoff threshold, r such that, at the margin, we are willing to automatically dispatch r ambulances when they aren't needed in order to send one ambulance when it is needed, then we want

$$\frac{\Delta FP}{\Delta TP} \leq r$$

which makes the binary version of our loss function $FP - r \cdot TP$, and the continuous version equivalent to the α -weighted cross-entropy loss function.

$$J = - \sum_{i=1}^N \alpha y_i \log(p_i) + (1 - \alpha)(1 - y_i) \log(1 - p_i), \quad \alpha = \frac{r}{r + 1}$$

Why are these equivalent?

Adding a constant to the loss function, or multiplying it by a positive constant, does not change its effect, because in comparing one iteration of the model to another, the algorithm is only concerned with which has the smaller loss.

The binary loss function $FP - r \cdot TP$ is equivalent to $FP - r \cdot TP + (TN + FP)$, because $TN + FP$ is constant, so $FP - r \cdot TP$ is equivalent to $-(r \cdot TP + TN)$.

$$\begin{aligned} & FP - r \cdot TP \\ & -(r \cdot TP + TN) \end{aligned}$$

Multiplying by $\frac{1}{r+1}$ gives an equivalent loss function, because $\frac{1}{r+1} > 0$.

$$\begin{aligned} & -\frac{r \cdot TP + TN}{r + 1} \\ & -\left(\frac{r}{r + 1}TP + \frac{1}{r + 1}TN\right) \\ & -\left(\frac{r}{r + 1}TP + \left(1 - \frac{r}{r + 1}\right)TN\right) \\ & -(\alpha TP + (1 - \alpha)TN) \end{aligned}$$

The continuous version of TP and TN are $\sum_{i=1}^N y_i \log(p_i)$ and $\sum_{i=1}^N (1 - y_i) \log(1 - p_i)$, so we get the α -weighted binary cross-entropy loss function,

$$J = - \sum_{i=1}^N \alpha y_i \log(p_i) + (1 - \alpha)(1 - y_i) \log(1 - p_i), \quad \alpha = \frac{r}{r + 1}$$

In training our models we will consider different values for the ethical tradeoff rate r . A very small rate, like $r = 1$ may be ethically justifiable, since our model is recommending whether to send an ambulance *now*, without waiting for more information from eyewitnesses, and police can reassess when they have more information. We will test $r = 1$, $r = 10$, and the rate of class imbalance in the data, about $r = 5$.

3.7. Model Evaluation: Technical Considerations

In the supervised learning method we used here, for each of the $\approx 600,000$ samples (people) in the dataset, we know the answer (the *label* or *ground truth*) to the question, whether the person needed an ambulance, $y = 0$ for “no” and $y = 1$ for “yes.” We are trying use historical data to build a model to predict the label for new data (incoming automated crash notifications).

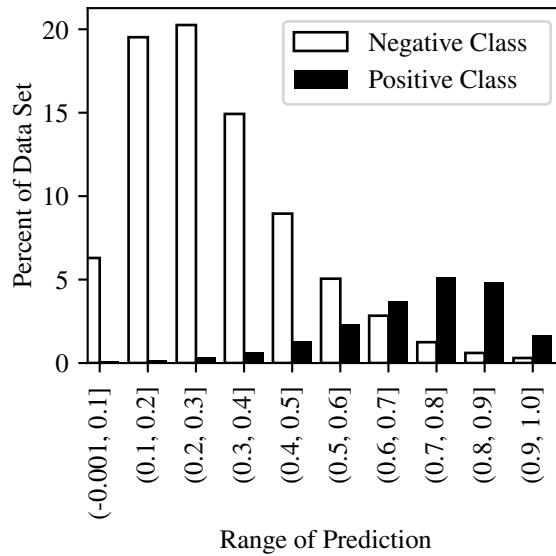
The binary classification models we used return, for each sample, a continuous probability $p \in (0, 1)$ that the sample belongs in the positive class. If a sample has $p = 0.1$, the model is 90% confident that this sample is in the negative class. We then pick a threshold, usually but not necessarily 0.5, and make a binary prediction, that samples with $p \geq 0.5$ need an ambulance, and those with $p < 0.5$ do not. The *loss function* used by the model is the sum

not of how many binary predictions were incorrect, but how strongly incorrect the continuous predictions were. If the prediction for a sample is $p = 0.3$ and the label is $y = 0$, then the loss for that sample is 0.3, but if its label were $y = 1$, then the loss would be 0.7.

A perfect model would not only predict each sample's label correctly, but would do it with perfect certainty. In the real world, with interesting questions about real data, we will have false positives ($y = 0$ and $p > 0.5$) and false negatives ($y = 1$ and $p < 0.5$), but we hope those are few, and that the predictions are strongly correct, meaning the predictions are close to their labels.

When we get results for our models based on crash data, we need some frame of reference for what is "good" and "bad," so we have created two sets of entirely artificial results using a gamma distribution for ideal results and a uniform distribution for awful results.

The histogram below of the percent of samples with predictions p in each range illustrates the best results we can hope for in the real world. The positive class is small because the data is imbalanced. There are some false positives and negatives, but the overwhelming majority of the predictions are correct, and most with strong confidence.



The *confusion matrix* for this ideal data set, here given as percentages of the entire dataset, shows few false positives and false negatives.

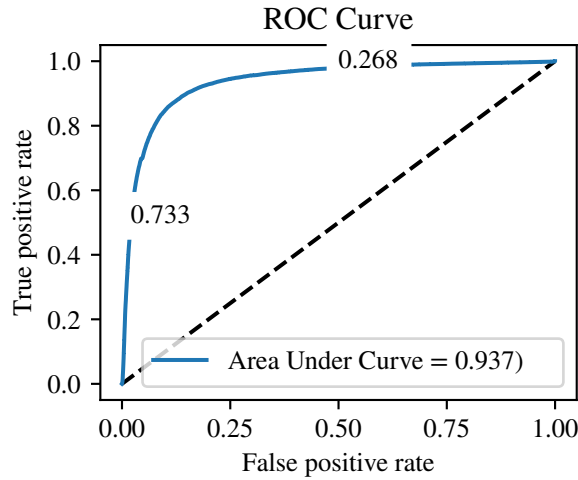
		Prediction	
		N	P
Actual	N	70.0%	10.0%
	P	2.4%	17.6%

These metrics are the ones we will watch when evaluating models. Each of them tells a different story about what the model does well.

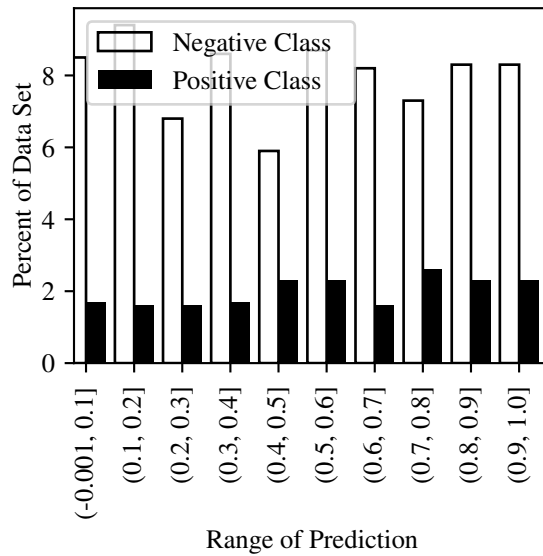
0.875	Accuracy
0.876	Balanced Accuracy
0.636	Precision
0.875	Balanced Precision
0.878	Recall
0.738	F1
0.876	Balanced F1
0.746	Gmean

The Receiver Operating Characteristic (ROC) is a parameterized curve following the probability threshold from $p = 0$ to $p = 1$, plotting the true positive rate (TPR) versus the false positive rate (FPR). The Area Under the ROC curve (AUC) is often used to compare two models, with AUC of 1 indicating perfect prediction and AUC of 0.5 indicating no discernable pattern.

We have added to the typical ROC curve two labels, one for the positive and one for the negative class, of the median of the probabilities of the samples in that class. The further apart those numbers are, the more robust the model.



In the ideal results above, the data had a pattern that the algorithm learned while building the model. The results below illustrate the worst case scenario, where the algorithm does not learn a good model, usually because the data does not have a pattern that predicts the target variable. In the ROC curve, the median values of the probabilities for the two classes are so close that the labels are on top of each other.

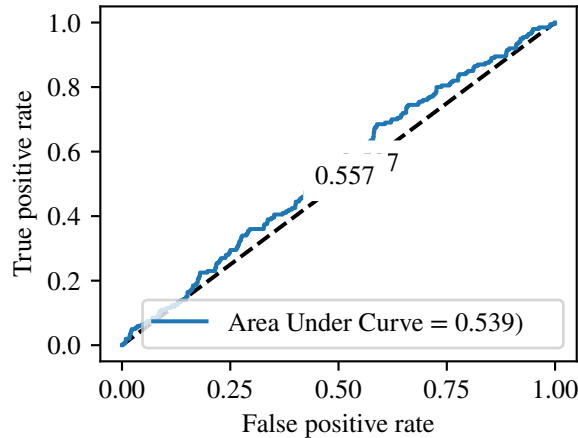


		Prediction	
		N	P
Actual	N	39.2%	40.8%
	P	8.9%	11.1%

Ambulance Dispatch

0.503	Accuracy
0.522	Balanced Accuracy
0.214	Precision
0.521	Balanced Precision
0.555	Recall
0.309	F1
0.538	Balanced F1
0.324	Gmean

ROC Curve



3.8. Model Evaluation: Incorporating Ethical Tradeoffs

In evaluating our models, the considerations are not just technical. A false positive is a recommendation to send an ambulance when one is not needed, which costs money. A false negative is a recommendation to not send an ambulance when one is needed, which costs lives.

Of the metrics we are watching, F1 and AUC seem most useful in discriminating “better” from “worse” models. F1 is the harmonic mean of Precision (What proportion of the ambulances we sent were needed?) and Recall (What proportion of the ambulances needed did we send?), and reflects the discrete results. AUC (Area Under the (ROC) Curve) quantifies the predictive power of the continuous results. It is possible to introduce a parameter to weight the precision and recall parts of F1 if you can quantify how much more important one is than the other, but we had no way to choose that number.

4. Results

5. Conclusions

6. Discussion

7. Future Work

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 the link in the references.

8.

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

- Aloul, F., Zualkernan, I., Abu-Salma, R., Al-Ali, H., Al-Merri, M., 2014. ibump: Smartphone application to detect car accidents. 2014 International Conference on Industrial Automation, Information and Communications Technology, Industrial Automation, Information and Communications Technology (IAICT), 2014 International Conference on , 52 – 56URL: <https://ezproxyprod.ucs.louisiana.edu:2443/login?url=https://search.ebscohost.com/login.aspx?direct=true&AuthType=ip,cookie,uid,url&db=edsee&AN=edsee.6922107&site=eds-live&scope=site>.
- Basso, F., Pezoa, R., Varas, M., Villalobos, M., 2021. A deep learning approach for real-time crash prediction using vehicle-by-vehicle data. *Accident Analysis & Prevention* 162, 106409. URL: <https://www.sciencedirect.com/science/article/pii/S0001457521004401>, doi:<https://doi.org/10.1016/j.aap.2021.106409>.
- BlinkApp LLC, . Blink! URL: <https://www.blinkapp.net>.
- Breiman, L., 1996. Bagging predictors. *Machine Learning* 24. URL: <https://doi.org/10.1007/BF00058655>.
- Cai, Q., Abdel-Aty, M., Yuan, J., Lee, J., Wu, Y., 2020. Real-time crash prediction on expressways using deep generative models. *Transportation Research Part C: Emerging Technologies* 117, 102697. URL: <https://www.sciencedirect.com/science/article/pii/S0968090X20306124>, doi:<https://doi.org/10.1016/j.trc.2020.102697>.
- Chawla, N., Bowyer, K., Hall, L., Kegelmeyer, W., 2002. Smote: Synthetic minority over-sampling technique. *JOURNAL OF ARTIFICIAL INTELLIGENCE RESEARCH* 16, 321 – 357.
- Chen, T., Lu, Y., Fu, X., Sze, N., Ding, H., 2022a. A resampling approach to disaggregate analysis of bus-involved crashes using panel data with excessive zeros. *Accident Analysis & Prevention* 164, 106496. URL: <https://www.sciencedirect.com/science/article/pii/S0001457521005273>, doi:<https://doi.org/10.1016/j.aap.2021.106496>.
- Chen, T., Shi, X., Wong, Y.D., Yu, X., 2020. Predicting lane-changing risk level based on vehicles' space-series features: A pre-emptive learning approach. *Transportation Research Part C: Emerging Technologies* 116, 102646. URL: <https://www.sciencedirect.com/science/article/pii/S0968090X20305611>, doi:<https://doi.org/10.1016/j.trc.2020.102646>.
- Chen, Z., Liu, K., Wang, J., Yamamoto, T., 2022b. H-convlstm-based bagging learning approach for ride-hailing demand prediction considering imbalance problems and sparse uncertainty. *Transportation Research Part C: Emerging Technologies* 140, 103709. URL: <https://www.sciencedirect.com/science/article/pii/S0968090X22001474>, doi:<https://doi.org/10.1016/j.trc.2022.103709>.
- Elamrani Abou Elassad, Z., Mousannif, H., Al Moatassime, H., 2020. A real-time crash prediction fusion framework: An imbalance-aware strategy for collision avoidance systems. *Transportation Research Part C: Emerging Technologies* 118, 102708. URL: <https://www.sciencedirect.com/science/article/pii/S0968090X20306239>, doi:<https://doi.org/10.1016/j.trc.2020.102708>.
- Formosa, N., Quddus, M., Ison, S., Abdel-Aty, M., Yuan, J., 2020. Predicting real-time traffic conflicts using deep learning. *Accident Analysis & Prevention* 136, 105429. URL: <https://www.sciencedirect.com/science/article/pii/S000145751930973X>, doi:<https://doi.org/10.1016/j.aap.2019.105429>.
- Freund, Y., Schapire, R.E., 1997. A decision-theoretic generalization of on-line learning and an application to boosting. *Journal of Computer and System Sciences* 55, 119–139. URL: <https://www.sciencedirect.com/science/article/pii/S002200099791504X>, doi:<https://doi.org/10.1006/jcss.1997.1504>.
- Google, . Get help after a car crash (pixel 6 pro). URL: https://partnerdash.google.com/apps/simulator/#get-help-after-a-car-crash?l=en&model=Pixel_6_Pro.
- Guo, M., Zhao, X., Yao, Y., Yan, P., Su, Y., Bi, C., Wu, D., 2021. A study of freeway crash risk prediction and interpretation based on risky driving behavior and traffic flow data. *Accident Analysis & Prevention* 160, 106328. URL: <https://www.sciencedirect.com/science/article/pii/S0001457521003596>, doi:<https://doi.org/10.1016/j.aap.2021.106328>.
- Haule, H.J., Ali, M.S., Alluri, P., Sando, T., 2021. Evaluating the effect of ramp metering on freeway safety using real-time traffic data. *Accident Analysis & Prevention* 157, 106181. URL: <https://www.sciencedirect.com/science/article/pii/S0001457521002128>, doi:<https://doi.org/10.1016/j.aap.2021.106181>.
- Herbert, G., 2019. Crash Report Sampling System: Imputation. Technical Report DOT HS 812 795. National Highway Traffic Safety Administration.
- Islam, Z., Abdel-Aty, M., Cai, Q., Yuan, J., 2021. Crash data augmentation using variational autoencoder. *Accident Analysis & Prevention* 151, 105950. URL: <https://www.sciencedirect.com/science/article/pii/S000145752031770X>, doi:<https://doi.org/10.1016/j.aap.2020.105950>.
- Jiang, F., Yuen, K.K.R., Lee, E.W.M., 2020. A long short-term memory-based framework for crash detection on freeways with traffic data of different temporal resolutions. *Accident Analysis & Prevention* 141, 105520. URL: <https://www.sciencedirect.com/science/article/pii/S0001457519317713>, doi:<https://doi.org/10.1016/j.aap.2020.105520>.

- Khan, W.A., Ma, H.L., Chung, S.H., Wen, X., 2021. Hierarchical integrated machine learning model for predicting flight departure delays and duration in series. *Transportation Research Part C: Emerging Technologies* 129, 103225. URL: <https://www.sciencedirect.com/science/article/pii/S0968090X21002394>, doi:<https://doi.org/10.1016/j.trc.2021.103225>.
- King, G., Zeng, L., 2001. Logistic regression in rare events data. *Political Analysis* 9, 137 – 163.
- Lack, C.D., Berkow, K.S., Gao, Y., 2021. Insights into motor carrier crashes: A preliminary investigation of fmcsa inspection violations. *Accident Analysis & Prevention* 155, 106105. URL: <https://www.sciencedirect.com/science/article/pii/S0001457521001366>, doi:<https://doi.org/10.1016/j.aap.2021.106105>.
- Li, P., Abdel-Aty, M., Yuan, J., 2020. Real-time crash risk prediction on arterials based on lstm-cnn. *Accident Analysis & Prevention* 135, 105371. URL: <https://www.sciencedirect.com/science/article/pii/S0001457519311108>, doi:<https://doi.org/10.1016/j.aap.2019.105371>.
- Li, Y., Li, M., Yuan, J., Lu, J., Abdel-Aty, M., 2021. Analysis and prediction of intersection traffic violations using automated enforcement system data. *Accident Analysis & Prevention* 162, 106422. URL: <https://www.sciencedirect.com/science/article/pii/S000145752100453X>, doi:<https://doi.org/10.1016/j.aap.2021.106422>.
- Lin, T.Y., Goyal, P., Girshick, R., He, K., Dollár, P., 2017. Focal loss for dense object detection, in: *Proceedings of the IEEE international conference on computer vision*, pp. 2980–2988.
- Lin, Y., Li, L., Jing, H., Ran, B., Sun, D., 2020. Automated traffic incident detection with a smaller dataset based on generative adversarial networks. *Accident Analysis & Prevention* 144, 105628. URL: <https://www.sciencedirect.com/science/article/pii/S0001457519314150>, doi:<https://doi.org/10.1016/j.aap.2020.105628>.
- Liu, Y., Lyu, C., Liu, Z., Cao, J., 2021. Exploring a large-scale multi-modal transportation recommendation system. *Transportation Research Part C: Emerging Technologies* 126, 103070. URL: <https://www.sciencedirect.com/science/article/pii/S0968090X21000954>, doi:<https://doi.org/10.1016/j.trc.2021.103070>.
- Man, C.K., Quddus, M., Theofilatos, A., 2022. Transfer learning for spatio-temporal transferability of real-time crash prediction models. *Accident Analysis & Prevention* 165, 106511. URL: <https://www.sciencedirect.com/science/article/pii/S000145752100542X>, doi:<https://doi.org/10.1016/j.aap.2021.106511>.
- Mohammadi, R., He, Q., Ghofrani, F., Pathak, A., Aref, A., 2019. Exploring the impact of foot-by-foot track geometry on the occurrence of rail defects. *Transportation Research Part C: Emerging Technologies* 102, 153–172. URL: <https://www.sciencedirect.com/science/article/pii/S0968090X18314001>, doi:<https://doi.org/10.1016/j.trc.2019.03.004>.
- Morris, C., Yang, J.J., 2021. Effectiveness of resampling methods in coping with imbalanced crash data: Crash type analysis and predictive modeling. *Accident Analysis & Prevention* 159, 106240. URL: <https://www.sciencedirect.com/science/article/pii/S0001457521002712>, doi:<https://doi.org/10.1016/j.aap.2021.106240>.
- National Center for Statistics and Analysis, 2022. Crash Report Sampling System analytical user’s manual, 2016–2020. Technical Report DOT HS 813 236. National Highway Traffic Safety Administration.
- NHTSA, 2016–2020. Crash report sampling system. <https://www.nhtsa.gov/crash-data-systems/crash-report-sampling-system>.
- Orsini, F., Gecchele, G., Rossi, R., Gastaldi, M., 2021. A conflict-based approach for real-time road safety analysis: Comparative evaluation with crash-based models. *Accident Analysis & Prevention* 161, 106382. URL: <https://www.sciencedirect.com/science/article/pii/S0001457521004139>, doi:<https://doi.org/10.1016/j.aap.2021.106382>.
- Park, H., Oh, C., 2019. A vehicle speed harmonization strategy for minimizing inter-vehicle crash risks. *Accident Analysis & Prevention* 128, 230–239. URL: <https://www.sciencedirect.com/science/article/pii/S0001457519300314>, doi:<https://doi.org/10.1016/j.aap.2019.04.014>.
- Parsa, A.B., Taghipour, H., Derrible, S., Mohammadian, A.K., 2019. Real-time accident detection: Coping with imbalanced data. *Accident Analysis & Prevention* 129, 202–210. URL: <https://www.sciencedirect.com/science/article/pii/S0001457519301642>, doi:<https://doi.org/10.1016/j.aap.2019.05.014>.
- Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., Duchesnay, E., 2011. Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research* 12, 2825–2830.
- Peng, Y., Li, C., Wang, K., Gao, Z., Yu, R., 2020. Examining imbalanced classification algorithms in predicting real-time traffic crash risk. *Accident Analysis & Prevention* 144, 105610. URL: <https://www.sciencedirect.com/science/article/pii/S0001457519306906>, doi:<https://doi.org/10.1016/j.aap.2020.105610>.
- Rahman, M., 2019. Google accidentally rolls out “personal safety” app, confirming car crash detection is coming to the pixel. URL: <https://www.xda-developers.com/google-pixel-car-crash-detection/>.
- Schlögl, M., 2020. A multivariate analysis of environmental effects on road accident occurrence using a balanced bagging approach. *Accident Analysis & Prevention* 136, 105398. URL: <https://www.sciencedirect.com/science/article/pii/S0001457519308516>, doi:<https://doi.org/10.1016/j.aap.2019.105398>.
- Schlögl, M., Stütz, R., Laaha, G., Melcher, M., 2019. A comparison of statistical learning methods for deriving determining factors of accident occurrence from an imbalanced high resolution dataset. *Accident Analysis & Prevention* 127, 134–149. URL: <https://www.sciencedirect.com/science/article/pii/S0001457518307760>, doi:<https://doi.org/10.1016/j.aap.2019.02.008>.
- Shi, Q., Zhang, H., 2021. An improved learning-based lstm approach for lane change intention prediction subject to imbalanced data. *Transportation Research Part C: Emerging Technologies* 133, 103414. URL: <https://www.sciencedirect.com/science/article/pii/S0968090X21004083>, doi:<https://doi.org/10.1016/j.trc.2021.103414>.
- Shi, X., Wong, Y.D., Li, M.Z.F., Palanisamy, C., Chai, C., 2019. A feature learning approach based on xgboost for driving assessment and risk prediction. *Accident Analysis & Prevention* 129, 170–179. URL: <https://www.sciencedirect.com/science/article/pii/S0001457518310820>, doi:<https://doi.org/10.1016/j.aap.2019.05.005>.
- Sosmart SAP, . SOSmart automatic car crash detection app. URL: <http://www.sosmartapp.com>.

- Tomek, I., 1976. Two modifications of cnn. *IEEE transactions on Systems, Man and Communications*, SMC 6, 769–772.
- White, J., Thompson, C., Turner, H., Dougherty, B., Schmidt, D.C., 2011. Wreckwatch: Automatic traffic accident detection and notification with smartphones. *MOBILE NETWORKS AND APPLICATIONS* 16, 285 – 303. URL: <https://ezproxyprod.ucs.louisiana.edu:2443/login?url=https://search.ebscohost.com/login.aspx?direct=true&AuthType=ip,cookie,uid,url&db=edsbl&AN=RN290973892&site=eds-live&scope=site>.
- Winkler, R., 2021. Apple wants iphones to detect car crashes, auto-dial 911. *The Wall Street Journal Eastern Edition*, 1 URL: <https://ezproxyprod.ucs.louisiana.edu:2443/login?url=https://search.ebscohost.com/login.aspx?direct=true&AuthType=ip,cookie,uid,url&db=edsgao&AN=edsgcl.681029711&site=eds-live&scope=site>.
- Yahaya, M., Guo, R., Fan, W., Bashir, K., Fan, Y., Xu, S., Jiang, X., 2021a. Bayesian networks for imbalance data to investigate the contributing factors to fatal injury crashes on the ghanaian highways. *Accident Analysis & Prevention* 150, 105936. URL: <https://www.sciencedirect.com/science/article/pii/S0001457520317565>, doi:<https://doi.org/10.1016/j.aap.2020.105936>.
- Yahaya, M., Guo, R., Jiang, X., Bashir, K., Matara, C., Xu, S., 2021b. Ensemble-based model selection for imbalanced data to investigate the contributing factors to multiple fatality road crashes in ghana. *Accident Analysis & Prevention* 151, 105851. URL: <https://www.sciencedirect.com/science/article/pii/S0001457520316717>, doi:<https://doi.org/10.1016/j.aap.2020.105851>.
- Yu, R., Wang, Y., Zou, Z., Wang, L., 2020. Convolutional neural networks with refined loss functions for the real-time crash risk analysis. *Transportation Research Part C: Emerging Technologies* 119, 102740. URL: <https://www.sciencedirect.com/science/article/pii/S0968090X20306549>, doi:<https://doi.org/10.1016/j.trc.2020.102740>.
- Zhu, S., Wan, J., 2021. Cost-sensitive learning for semi-supervised hit-and-run analysis. *Accident Analysis & Prevention* 158, 106199. URL: <https://www.sciencedirect.com/science/article/pii/S000145752100230X>, doi:<https://doi.org/10.1016/j.aap.2021.106199>.