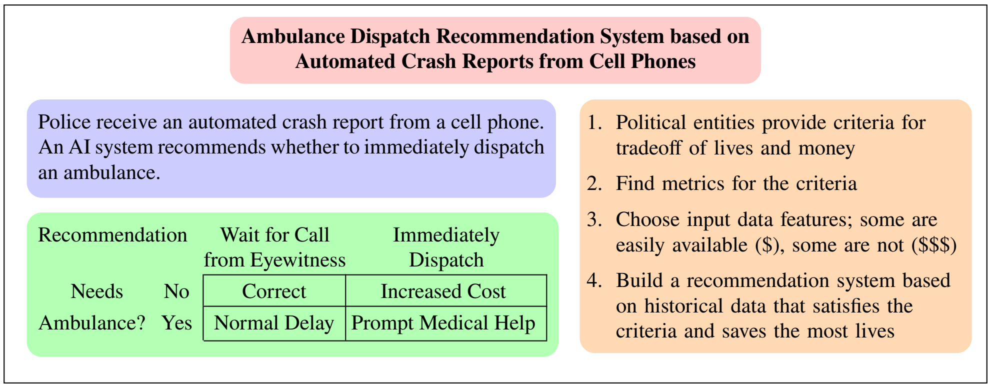
Graphical Abstract

Ambulance Dispatch Recommendation System based on Automated Crash Reports from Cell Phones

J. Bradford Burkman,Chee-Hung Henry Chu,Miao Jin,Malek Abuhijleh,Xiaoduan Sun



Ambulance Dispatch Recommendation System based on Automated Crash Reports from Cell Phones

Police receive an automated crash report from a cell phone. An AI system recommends whether to immediately dispatch an ambulance.

Recommendation		Wait for Call from Eyewitness	Immediately Dispatch
Needs	No	Correct	Increased Cost
Ambulance?	Yes	Normal Delay	Prompt Medical Help

1. Political entities provide criteria for tradeoff of lives and money
2. Find metrics for the criteria
3. Choose input data features; some are easily available ($), some are not ($$$)
4. Build a recommendation system based on historical data that satisfies the criteria and saves the most lives

Highlights

Ambulance Dispatch Recommendation System 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 made public (on GitHub) the code we used to perform the analysis on data from the Crash Report Sampling System (CRSS) and all of the output data.
- Novel Application motivated by Emerging Technology: Machine learning classification models for dispatching ambulances based on automated crash reports from cell phones.
- New Use of Dataset: We used the Crash Report Sampling System (CRSS), which has imputed missing values for some features, but not for all of the features 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, then compared the results with other imputation methods.
- Explicit Incorporation of Imbalanced Costs: False Positives give additional cost, False Negatives give delayed medical care.
- Explicit Incorporation of Political Dimensions: Framing the decision threshold as a government budget question.
- Consideration of Marginal Effects of Threshold Shifting
- Perennial Machine Learning Challenge: Imbalanced Datasets

Ambulance Dispatch Recommendation System 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

Some new cell 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 has some system that recommends 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 value $p \in [0, 1]$ that increases with the probability that the person needs an ambulance. Using a decision threshold θ, 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.

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 the decision threshold θ is ethically problematic, but governments make such a tradeoff when they set budgets for emergency services.

We consider and interpret three options for the decision threshold θ based on the political consideration, "How much will it cost?" How many automated ambulance dispatches are we willing to fund (FP + TP) for each one of them that is actually needed (TP)? We will explore two versions of that question, the total and the marginal.

We show that the quality of the model depends highly on the input data available, having considered three levels of data availability. The "Easy" level includes data the emergency dispatcher has before the notification, like time of day and weather. The "Medium" level adds information about the location and information from the cell service provider about the user, like the age and sex. The "Hard" level adds information that requires having access to records 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. Scenario

In the (fictitious) city of Springfield, the city council and mayor are debating whether to immediately dispatch ambulances based on automated notifications from cell phones. Many residents have cell phones (iPhones and Google

bradburkman@gmail.com (J.B. Burkman)
http://www.github.com/bburkman/Ambulance_Dispatch (J.B. Burkman)
ORCID(s):

Pixels) whose accelerometers will detect the deceleration profile of a crash and automatically notify the emergency call center, which immediately dispatches a police officer. The city leaders are pleased that, because of the automated notifications, the police response to the crash scene is faster. Should they also immediately dispatch an ambulance, making the medical response faster?

Traditionally, the emergency call center did not know about a crash until an eyewitness called, and the eyewitness could say whether the crash persons needed an ambulance, but that information does not come with an automated crash notification from a cell phone. The notification will come with a location, the emergency dispatcher already has some information (time of day, day of week, weather, urbanicity), and the cell service provider may provide some information about the primary user of the cell phone (age, sex). With that information, the emergency dispatcher has three options.

Always immediately dispatch an ambulance, most of which will not be needed

Never immediately dispatch an ambulance; instead, wait for a call from an eyewitness. Many of the ambulances eventually sent to crashes had a cell phone notification and could have been sent sooner.

Sometimes Develop and implement an AI recommendation system to decide which to send immediately, reserving the option to send an ambulance later based on information from an eyewitness.

In Springfield today, without immediate ambulance dispatch based on automated crash notifications from cell phones, 50% of dispatched ambulances go to automobile crashes and 10% of crash persons need an ambulance. Twenty percent of the crashes first have an automated notification from a cell phone before a call from an eyewitness telling whether or not the crash person needs an ambulance. The other 80% of crashes only have an eyewitness call. Of the crashes with automated notifications from cell phones, 15% will need an ambulance, and 85% will not. In Figure 1 we have scaled the numbers per 100 ambulances sent before implementation of immediate ambulance dispatch.

[We chose these numbers for clarity of illustration; an actual implementation would use local data. For details on the 85/15 split, see §2.2 Dataset and §5 Simplifying Assumptions.]

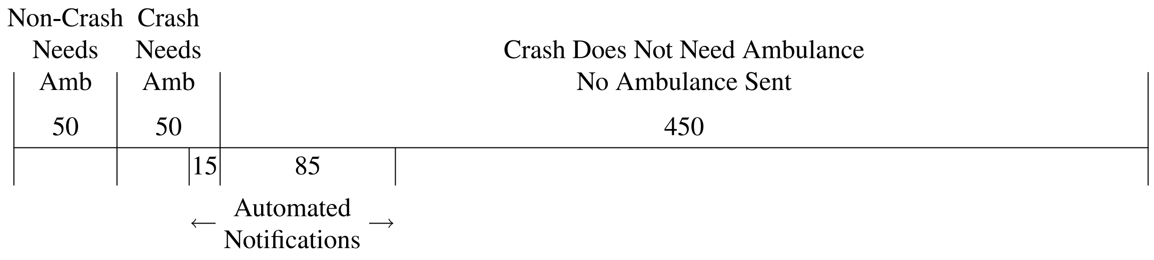


Figure 1: Springfield before implementing immediate dispatch of ambulances. Figure accompanies §1.1

If Springfield were to implement an AI recommendation system to immediately dispatch ambulances based on automated calls from cell phones, the recommendations would not perfectly predict which crash persons need an ambulance. See Figure 2, where we have zoomed in on the left side of Figure 1. In our per-100-ambulances-currently-sent proportions, the recommendation system would classify each of the automated notifications as needing or not needing an ambulance.

Of the fifteen automated crash notifications that need an ambulance, the system would correctly classify some of them as needing an ambulance (True Positive, TP), and those crash persons would get medical attention more promptly, which is the goal and benefit of the recommendation system. The rest of those fifteen would be incorrectly classified as probably not needing an ambulance with a recommendation to wait for a call from an eyewitness before sending one (False Negative, FN). Note that the false negatives get an ambulance just as quickly under the new system as under the old, with an ambulance dispatched upon call from an eyewitness.

Of the 85 automated notifications that do not need an ambulance, some would be correctly classified (True Negative, TN), but some would be incorrectly classified and we would immediately dispatch an unneeded ambulance (False Positive, FP). Besides the cost of administration, those additional ambulance runs are the cost of immediately dispatching ambulances. In the short term those additional ambulance runs could be more than current resources (ambulances and their teams) could handle, and in the long term could be unacceptably expensive.

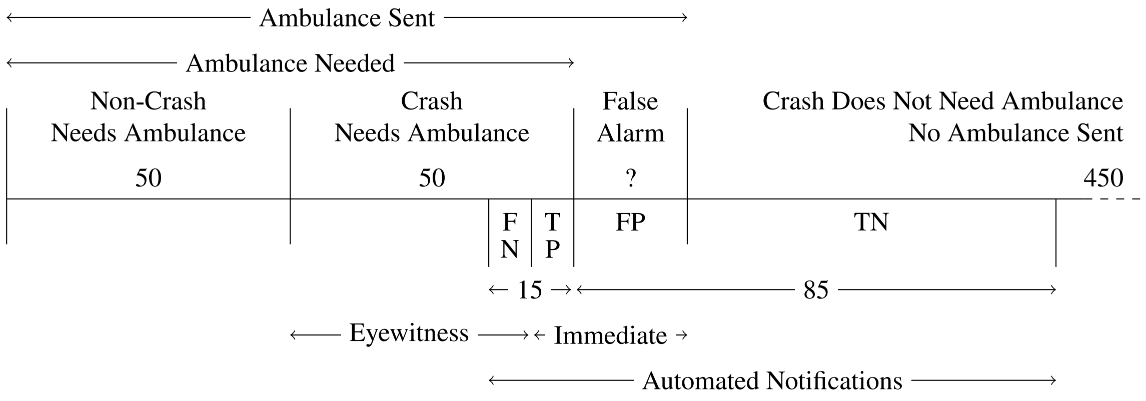


Figure 2: Springfield after implementing immediate dispatch of ambulances. Figure accompanies §1.1

The leaders of Springfield need to choose a balance between the benefit of more prompt medical attention and the cost of sending more ambulances. The tradeoff of lives and money is not ethically or morally comfortable, but that is the choice governments make when they set budgets for health care and emergency services. In the confusion matrices in Figure 3, Springfield would love to increase TP without increasing FP, but the recommendation system will not give perfect predictions.

		Prediction	
		PN	PP
Actual	N	TN	FP
	P	FN	TP

Recommendation		Wait for Call from Eyewitness	Immediately Dispatch
Needs	No	Correct	Increased Cost
Ambulance?	Yes	Normal Delay	Prompt Medical Help

Figure 3: Confusion matrix for ambulance dispatch. Figure accompanies §1.1

Building Springfield's AI recommendation system starts with an historical dataset with the features the emergency dispatchers will have at the time of the automated notification, (time of day, weather, maybe age and sex, possibly more information) and whether that historical crash person needed an ambulance (supervised learning). A machine learning algorithm learns a model of the data, and when an automated crash notification comes in, given the data available, the model returns a value $p \in [0, 1]$ that increases with the probability that the crash person needs an ambulance. The city council and mayor need to choose a decision threshold θ such that if, for a particular crash notification, $p > \theta$, then immediately dispatch an ambulance; if $p < \theta$, wait for a call from an eyewitness. Choosing a decision threshold of $p = 1$ would mean never immediately dispatching an ambulance, and choosing $p = 0$ would be always; the town leaders want to know how to choose a p between the two extremes that fits their values and their budget.

The histogram in Figure 4 shows typical model output. The model generally gives lower p values to crash persons who do not need an ambulance (Neg) and higher p values to crash persons who do need an ambulance (Pos), but there is significant overlap. The most obvious feature of the histogram is the class imbalance, that there are many more Neg than Pos, in fact $85/15 \approx 6$ Neg for each Pos.

Given a choice of decision threshold θ, Springfield would immediately dispatch ambulances to all of the crashes with a p value to the right of θ. The Pos (Needs ambulance) to the right of θ would get more prompt medical attention (TP), but the Neg (Does not need ambulance) to the right of θ would be wasted ambulance runs (FP) . At $\theta = 0.8$, TP and FP are about equal, but as we consider smaller θ the number of TP increases by smaller and smaller amounts while the number of FP grows dramatically.

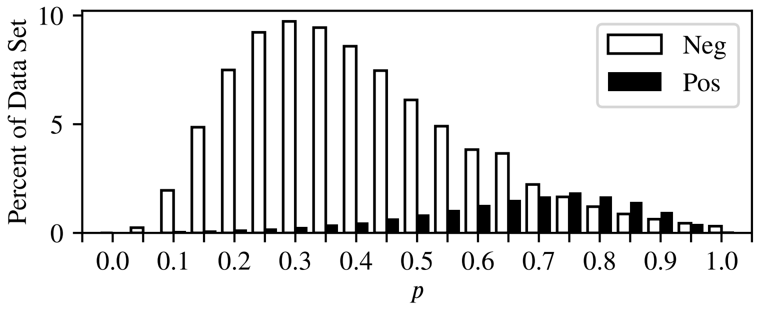


Figure 4: Example model test results. Figure accompanies §1.1

We will consider three ways the leaders of Springfield can think about how to choose θ, three metrics for political decision thresholds, detailed in §2.1.

1. Percent increase in number of ambulance calls
2. Percent of immediately dispatched ambulances that are actually needed
3. Minimum probability that an immediately dispatched ambulance is actually needed

1.2. Overview

In this paper we explore building a machine learning model to recommend whether to immediately dispatch an ambulance upon an automated notification from a cell phone rather than waiting for a call from an eyewitness.

Such a model would be trained on historical data. We have used the Crash Report Sampling System (CRSS) 2016-2021 data, and, in ways that we have not seen in the literature, recreated the method used by the authors of the dataset to impute missing values and compared it against other methods.

The criteria for the decision threshold (when to recommend immediately dispatching an ambulance) are political, not technical, decisions, and we posit three budgetary criteria and for each criterion have created a metric to serve as a decision threshold on the p returned by the model for a new crash. Two metrics measure the entire dataset on either side of the threshold, and one measures marginal effect at the threshold. We develop a method for measuring such marginal effects using the model output.

An automated crash notification from a cell phone will give the location, and perhaps some more information about the primary user of the phone, but the emergency dispatcher already has some useful information, like time of day and weather. If the notification comes with the identification of the phone's primary user, the system could be set up to instantaneously correlate with vehicle registration records to get more useful information, like make, model, and age of the car, but a more sophisticated system would be expensive. Would having better data increase the number of needed ambulances sent faster to crash scenes? We consider three sets of data features and compare the results of models trained on those features.

Since most crashes do not require an ambulance, the dataset is slightly imbalanced (5:1). We report on several methods we tried, with mixed success, to handle the imbalance.

To support transferability, we have used a public dataset and made public all of the code we used in our investigation and all of the output data. This paper gives some results to support the conclusions and invites the interested reader to explore the full results, tinker with the code, and use any of it to investigate further topics. Simplifying assumptions and opportunities for future research are given in §5.

2. Methods

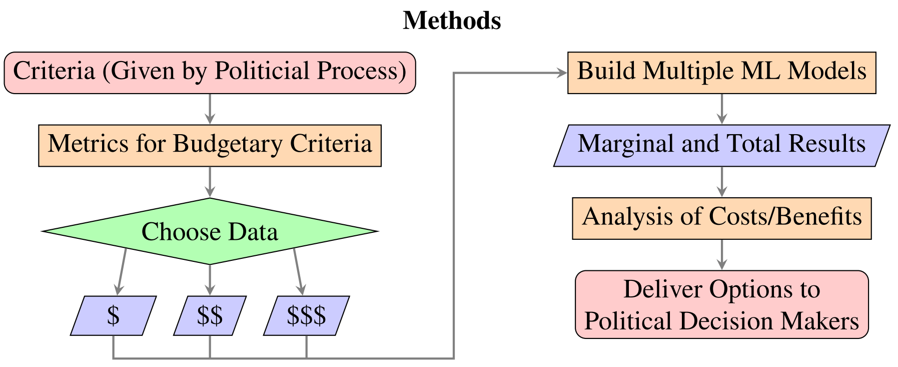

Methods
Criteria (Given by Politicial Process)
Metrics for Budgetary Criteria
Choose Data
$
$$
$$$
Build Multiple ML Models
Marginal and Total Results
Analysis of Costs/Benefits
Deliver Options to Political Decision Makers

Figure 5: Methods Graphical Abstract

2.1. Budgetary Decision Thresholds and Corresponding Metrics

Saying that we trade off lives for money makes us uncomfortable, but that is what governments do when they set budgets for health care and emergency services. All budgets are finite, and spending more money has diminishing returns, so we have to choose some criteria for our decision and accompanying metrics that let us quantify the criteria to choose an appropriate decision boundary for our recommendation system.

Our Springfield scenario illustrates the tradeoffs. We will consider three ways to set the decision threshold.

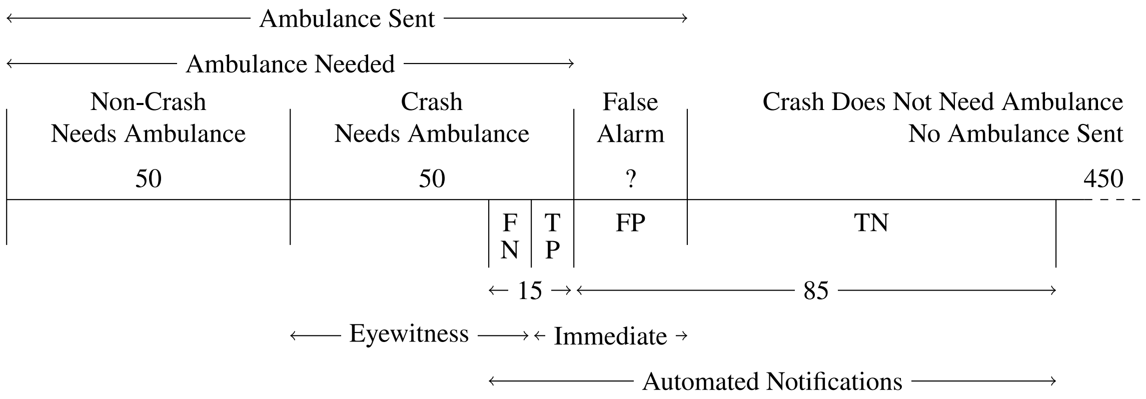


Figure 6: Springfield after implementing immediate dispatch of ambulances. Figure accompanies §1.1

2.1.1. Budgetary Decision Metric I: Percent Increased Number of Ambulance Calls

When a city or region implements immediate dispatch of ambulances, the number of ambulance dispatches increases by FP. Within the automated notifications, P = FN + TP ambulance runs becomes P + FP = FN + TP + FP ambulance runs, an increase by a rate of FP/P. The increase does not include the true positives (TP), because those ambulances would go eventually with or without immediate dispatch; the increase is the number of false positives (FP).

In the short term (too short to buy more ambulances and hire more teams), the existing budget can support an increase in the number of ambulance runs to crash persons by some small percentage. In the longer term, the city is willing to increase the budget to increase the number of ambulances going to crashes with automated notifications by a larger, but still fixed, percentage. We will use 5% as our example of how to implement this policy, setting the decision threshold θ where the number of false positives is 5% of the positive class.

$$\frac{\text{FP}}{\text{P}} = \frac{\text{FP}}{\text{FN} + \text{TP}} \leq 0.05 \tag{1}$$

In our Springfield scenario, scaling to 100 currently sent ambulances to crash or non-crash, the total number of ambulance runs goes from 100 to 100 + FP, a rate of increase of FP/100. For any city or region, if we knew the proportion of crashes with automated notifications from cell phones and the proportion of ambulances going to crashes, we could choose an FP/P threshold to match a budgetary decision criterion based on the increase in total number of ambulances sent to crashes or total number of ambulances sent to any situation.

2.1.2. *Budgetary Decision Metric II: Percent of Immediately Dispatched Ambulances Actually Needed*

A city or region is willing to immediately dispatch ambulances based on automated crash reports, but only up to the point where a certain proportion of the ambulances they immediately dispatch (PP = FP + TP) are actually needed (TP). This proportion, TP/(FP + TP) is called the *precision* of a machine learning model. In this paper we will use the term *precision* in this sense and *numerical precision* to describe the confidence we can have in a certain number of decimal places of a result.

To illustrate the method, we will choose Precision = 2/3, being willing to immediately dispatch one unnecessary ambulance for each two necessary ones.

$$\frac{\mathrm{TP}}{\mathrm{PP}} = \frac{\mathrm{TP}}{\mathrm{FP} + \mathrm{TP}} \geq \frac{2}{3} \tag{2}$$

2.1.3. *Budgetary Decision Metric III: Minimum Probability that Each Immediately Dispatched Ambulance is Needed*

The previous two decision criteria let the city leaders choose a specific dollar amount of increase in the annual ambulance budget, but for ethical reasons they may decide that, while they cannot afford to immediately dispatch an ambulance to every crash notification, they should immediately dispatch an ambulance to a crash notification with some probability (like 50% or 80%) of needing medical attention, and consider the total cost later. From our model results, can we find a decision threshold θ that corresponds to such a probability?

Our recommendation system will use a supervised-learning binary classification model trained on historical data. The models do not actually return a probability but return, for each sample, a value p that generally increases with the probability. For each sample we also know whether that historical crash person actually needed an ambulance (whether that sample is in the negative or positive class).

Consider a small band of values of p; the samples in that band are either in the negative or positive class. Call the number of negative and positive samples in the band Neg and Pos, to distinguish from the total number of samples in the negative and positive classes, N and P. The probability that a crash person in that band of p needs an ambulance is given by Pos/(Neg + Pos).

To illustrate the method, we will choose the minimum marginal probability to be 50%, meaning that each ambulance we immediately dispatch has at least a fifty percent chance of being needed.

$$\frac{\mathrm{Pos}}{\mathrm{Neg} + \mathrm{Pos}} \geq 0.5 \tag{3}$$

We can relate this metric to a familiar metric if we rephrase the probability as the ratio of needed to unneeded ambulances immediately dispatched. For instance, a 50% probability is a 1:1 ratio of needed to unneeded, and an 80% probability is a 4:1 ratio of needed to unneeded. The proportion of needed to unneeded ambulances sent in a neighborhood of p is proportional to a widely used metric, the slope of the ROC curve, with the constant of proportionality being the class ratio.

$$\frac{\mathrm{Pos}}{\mathrm{Neg}} = \frac{\Delta\mathrm{TP}}{\Delta\mathrm{FP}} = \frac{\mathrm{P}}{\mathrm{N}} \cdot \frac{\Delta\mathrm{TP}/\mathrm{P}}{\Delta\mathrm{FP}/\mathrm{N}} = \frac{\mathrm{P}}{\mathrm{N}} \cdot \frac{\Delta\mathrm{TPR}}{\Delta\mathrm{FPR}} = \frac{\mathrm{P}}{\mathrm{N}} \cdot m\mathrm{ROC} \tag{4}$$

2.2. Dataset

Ideally, we would use a dataset of crashes that spawned an automated notification, but we have not found such a dataset that is publicly available. Working with such a private dataset would be an important avenue of future research. (See §5 for a list of simplifying assumptions and opportunities for future research.)

We will use the Crash Report Sampling System (CRSS) data from 2016 to 2021. The CRSS is a curated sample of crashes in the US, weighted to more serious crashes such that 17% of the crash persons needed an ambulance, significantly more than the proportion of all reported crashes needing an ambulance. Since many low-speed crashes would have a crash profile similar to hard braking, they would not spawn an automated notification, so it is reasonable to assume that the set of crashes with automated notifications would have a higher percentage of persons needing an ambulance.

We make some simplifying assumptions (see §5) using this dataset, including that the class ratio (N:P) in the automated crash notification from cell phones will be close to that in the CRSS data, 5:1, and that the crash persons in the CRSS data are representative of the future crash persons whose cell phones send a crash notification. We will use the CRSS as a proxy for the set of crashes with automatic crash notifications, acknowledging that we do not know how good of a proxy it is. The primary merit of CRSS for our work is that it is publicly available so that our work can be critiqued, adapted, and expanded by others.

To prepare the data we had to bin (discretize) some features and to impute missing data. Some features in CRSS have both the original data with values signifying "Missing" or "Unknown" and a new feature with missing values imputed using IVEware (Raghunathan, Solenberger, Berglund and van Hoewyk), but not all of the features we wanted to use had imputed values. CRSS has a very useful document on the history of its imputation methods going back to 1988 with the predecessors of the current data set (Herbert, 2019). We debated the proper order of operations for binning and imputing, tried both, and decided to bin first, then impute. We tried several methods of imputation, including the IVEware used by the CRSS authors, but got better results using a round-robin random forest method. Full details and analysis are in the code, listed below.

We removed all crashes involving a pedestrian because deceleration profile of such a crash would be more like hard braking than hitting a large immovable object like a car or tree, so less likely to trigger an automated notification.

The dataset is slightly imbalanced, with five elements of the negative class for each element of the positive class. We considered several methods to handle the imbalance, including resampling, class weights, focal loss (Lin, Goyal, Girshick, He and Dollár, 2017), and balanced metrics. We cannot use the popular SMOTE oversampling method because our data is categorical (Chawla, Bowyer, Hall and Kegelmeyer, 2002). We tried undersampling with Tomek Links, but the resulting model results were not significantly different. The best results came from using the model algorithms from Imbalanced-Learn (Lemaître, Nogueira and Aridas, 2017), some of which apply bagging on top of algorithms from Scikit-Learn (Pedregosa, Varoquaux, Gramfort, Michel, Thirion, Grisel, Blondel, Prettenhofer, Weiss, Dubourg, Vanderplas, Passos, Cournapeau, Brucher, Perrot and Duchesnay, 2011).

After removing those pedestrian crashes we had 713,566 samples, each representing a crash person, and 78 relevant features. For details, see these sections of code in the `Keras` folder at
`www.github.com/bburkman/Ambulance_Dispatch`.

```
Ambulance_Dispatch_01_Get_Data.ipynb
Ambulance_Dispatch_02_Correlation.ipynb
Ambulance_Dispatch_03_Bin_Data.ipynb
Ambulance_Dispatch_04_Impute_Missing_Data.ipynb
Ambulance_Dispatch_05_IVEware_Order_of_Operations.ipynb
Ambulance_Dispatch_06_Build_Models_Tomek_Links.ipynb
```

2.3. Choosing Features

The `Accident`, `Vehicle`, and `Person` files of the CRSS dataset 2016-2021 have 170 unique features.

First we narrowed the features to those that are relevant, of good quality, and knowable at the time of the automated notification (before any eyewitness reports). Some features, like Vehicle Identification Number (VIN), have no predictive value. Other features have missing data for more than 20% of samples. Some features, like drug and alcohol test results, are unknowable at the time of the automated notification.

Having data available for instantaneous analysis when the crash notification arrives is not free, and some features are more expensive than others. A city thinking of implementing a recommendation system for immediate dispatch would need to decide how much to spend to have the data available, and whether the more expensive features increase the quality of the models enough to be worth the cost. We categorized the features as "Easy," "Medium," and "Hard," which can also be called "Free," "Expensive," and "Problematic." The "Easy" features are those the dispatcher already has, like day of week, time of day, weather, and urban/rural. The "Medium" features add details about the location (intersection, speed limit, interstate highway) and information the cell service company probably has about the primary user of the phone (age and sex). To have the medium features instantaneously available would require coordination of many resources and be expensive to set up. The "Hard" features are much more problematic, requiring more coordination of public and private records, and having that data readily available introduces privacy and data security concerns. Hard features include whether the location is a work zone, the likely vehicle driven by the primary user of the cell phone, and, if there are multiple automated notifications from the same location, how many crash persons are likely to be involved.

We note here our simplifying assumption (§5) that we will have complete and accurate data for each automated notification. Also, we will test three combinations of features but have not done more detailed testing to see which individual features or other groupings of features are most or least useful in predicting whether a crash person needs an ambulance.

See `Ambulance_Dispatch_01_Get_Data.ipynb` for a list of the excluded features.

See `Ambulance_Dispatch_03_Bin_Data.ipynb` for a list of the features we used for imputation of missing data in CRSS.

See `Ambulance_Dispatch_07_Build_Models.ipynb`. for the complete list of the features used in the Easy, Medium, and Hard model building.

2.4. Models

See `Ambulance_Dispatch_07_Build_Models.ipynb` for more details.

2.4.1. Binary Classification Algorithms and Hyperparameters

For each of the three sets of features we used eight binary classification algorithms, three of which take class weight α and one of which takes the focal loss parameter γ. (See Table 2.4.1) We learned models for various values of the hyperparameters, giving $3 \times 13 = 39$ different models. The $\alpha = 0.5$ class weight is the default, and the $\alpha = 0.85$ class weight balances the effect of the negative and positive class in the loss function, as 85% of the samples are in the negative class. Focal loss (Lin et al., 2017) puts more weight in the loss function on the samples that are badly classified, much like least squares regression puts more weight on the points furthest from the line. Setting $\gamma = 0.0$ has no effect; Lin's paper tested from $\gamma = 0.5$ to $\gamma = 5.0$ and recommended $\gamma = 2.0$.

Table 1
Models Tested for Recommendation System. Table accompanies §2.4.1

Model	Abbreviation	Source	Class Weight α	Focal Loss γ
AdaBoost Classifier	AdaBoost	Scikit-Learn		
Balanced Bagging Classifier	Bal Bag	Imbalanced-Learn		
Balanced Random Forest Classifier	Bal RF	Imbalanced-Learn	0.5	
			0.85	
Easy Ensemble Classifier with AdaBoost Estimator	Easy Ens	Imbalanced-Learn		
KerasClassifier with the Binary Focal Crossentropy loss function	Keras	Keras	0.5	0.0
			0.5	1.0
			0.5	2.0
			0.85	0.0
Logistic Regression Classifier	Log Reg	Scikit-Learn	0.5	
			0.85	
Random Forest Classifier	RF	Scikit-Learn		
RUSBoost Classifier	RUSBoost	Imbalanced-Learn		

2.4.2. Hyperparameter Effects

Our experience with varying the class weight and focal loss parameters was that they shifted the entire p distribution, both the positive and negative class, but did not do a better job of separating the positive and negative class, as measured by the area under the curve (AUC) of the receiver operating characteristic (ROC), as illustrated in Figure 7 below.

The KerasClassifier with the Binary Focal Crossentropy loss function takes both a class weight parameter α and a focal loss parameter γ. Varying these parameters gave us different shapes of distributions of p, but all three versions of the model on the hard features had ROC AUC between 0.7781 and 0.7785, a difference within the normal ranges of randomness in machine learning models.

If one is using the default decision threshold $\theta = 0.5$, then these hyperparameters are useful for shifting the distribution to meet the threshold, but since we are taking the liberty to move the threshold, varying the hyperparameters may be of little use. Since the ROC AUC quantifies how well the algorithm separates the positive and negative classes over the whole range of p, and we are most interested in a small range of p on the right end, the weights may yet have some useful effect, a topic for future investigation (§5).

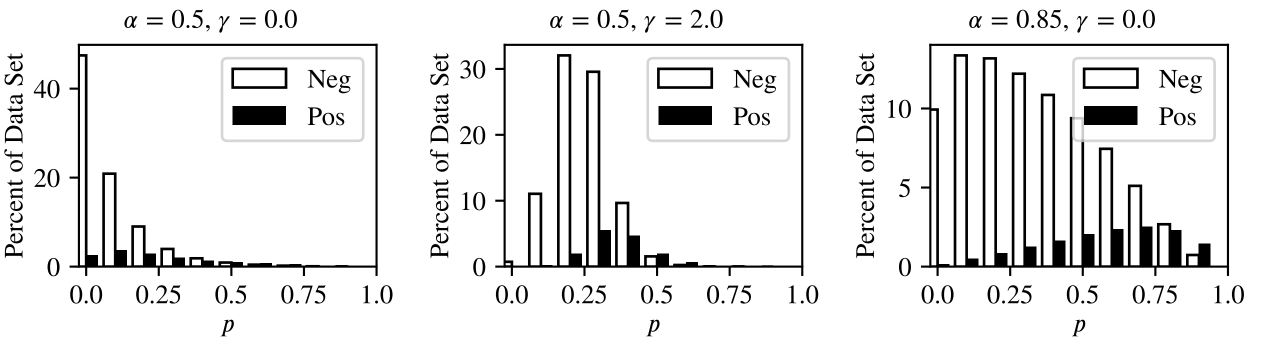


Figure 7: KerasClassifier with Different Hyperparameters. Figure accompanies §2.4.2

2.4.3. Five-Fold Cross Validation

As mentioned in §2.1.3, we need enough samples in each band of p to smooth out the randomness. If we had more samples total, we could use smaller bands and have more numerical precision in our specification of the decision threshold θ. If we used a typical 70/30 train/test split, we would only have p values for the 30% samples in the test set. Instead we used five-fold cross validation, having an 80/20 split five times, giving us p values for all of the samples.

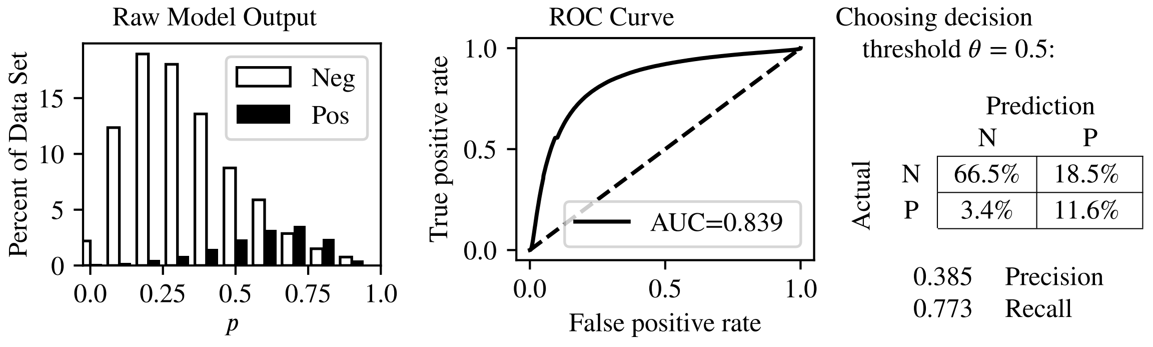
2.4.4. Interpreting Supervised Learning Binary Classification Results

In supervised learning binary classification, a model predicts, for each sample in the test set, whether the sample is in the negative or positive class. The model returns a value $p \in [0, 1]$, that increases with the probability that the sample is in the positive class. Additionally in supervised learning, we already know the answer to the question of whether the sample was in the negative or positive class, with $y \in \{0, 1\}$ given in the dataset but hidden from the model during the test phase. In the code, p is often called `y_proba` and y is called `y_test`. Using these two numbers, p and y, we can study, quantify, and illustrate how well the model predicts the actual values.

A perfect model would entirely separate the negative and positive classes, but the ideal we can hope for is that most of the negative elements are towards the left and most of the positive elements are towards the right of the distribution. In Figure 8, the data has the same class ratio as our CRSS data, with 85% in the negative class and 15% in the positive class. If we choose discrimination threshold $\theta = 0.5$, the value of p for which most models algorithms are optimized, the elements of the negative class with $p < \theta$ are True Negatives (TN), the elements of the negative class with $p > \theta$ are False Positives (FP), the elements of the positive class with $p < \theta$ are False Negatives (FN), and the elements of the positive class with $p > \theta$ are True Positives (TP).

If this ideal model were our recommendation system with $\theta = 0.5$, then 38.5% of the ambulances we immediately dispatched would be needed (Precision), and 73% of the needed ambulances would be immediately dispatched (Recall). If we chose a higher value of θ, we would increase TN, decrease FP, increase FN, and decrease TP. Recall would decrease, but the effect on precision is uncertain as FP and TP would both decrease.

The ROC (Receiver Operating Characteristic) curve is a parameterized curve showing the True Positive Rate (TP/P) versus the False Positive Rate (FP/N) as p varies from 0 (upper right) to 1 (lower left). The area under the curve (AUC) is widely used to compare the quality of models in terms of how well they separate the negative and positive classes over the entire range of $p \in [0, 1]$. For our work, however, given real-life budgetary constraints on expanding ambulance fleets, we are only interested in a small range of p on the right side of the distribution, so the ROC AUC is not the primary measure we will use to choose the best model.



	N	P
N	66.5%	18.5%
P	3.4%	11.6%

0.385 Precision
0.773 Recall

Figure 8: Example Model Results. Figure accompanies §2.4.4

2.5. Comparing Outputs of Different Models

2.5.1. Raw Model Outputs

The eight model algorithms not only give different results, but different kinds of results, and we have to find a way to compare them. See Figure 9. For the illustrations we have used models built on the Hard features with no class balance nor focal loss.

The ranges and shapes of the distributions are significantly different. The Balanced Bagging and Balanced Random Forest classifiers gives a nice spread from 0.0 to 1.0, but the AdaBoost, Easy Ensemble, and RUSBoost results are clustered in the middle, and the Random Forest on the left. If we used the Random Forest results with the default decision threshold $\theta = 0.5$, we would never immediately dispatch an ambulance. The KerasClassifier and Logistic Regression Classifier tend towards the left with long tails to the right.

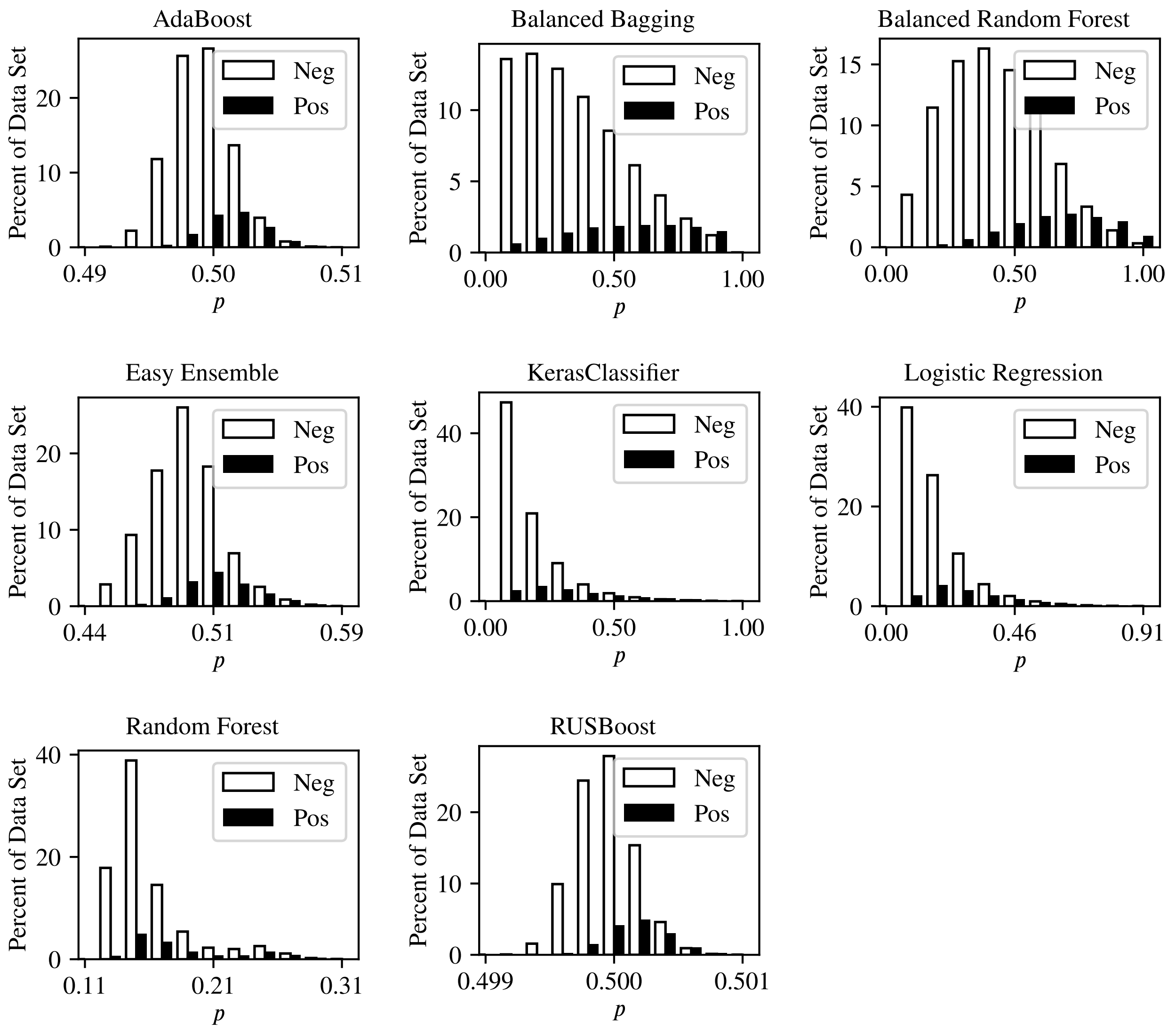


Figure 9: Raw Model Outputs. Figure accompanies §2.5.1

2.5.2. Numerics

We also need to be careful with the numerics, because the results could depend on how we slice p into intervals. Table 2 shows, for each of the eight classifiers with the hard features and no class weights nor focal loss, the number of samples (always 713,566), the number of unique values of p, the sum of the value counts of the ten (and hundred) most common values of p, the min and max of p, and the area under the ROC curve.

The p distribution from RUSBoost only ranges from 0.4990 to 0.5011, but within that 0.0021 range, the 713,566 samples have 706,938 unique values of p, which is as close to "continuous" as we can hope. On the other extreme, the Balanced Bagging distribution has only 270 unique values of p, and the ten most common values comprise 99% of the set, making it very discrete. Almost all of the values of p for Balanced Bagging are rounded to one decimal placeand 93% of the p values from Balanced Random Forest are rounded to two decimal places, which is important to acknowledge because we cannot claim to find a best value of θ with more precision than the outputs of the model.

The table gives the area under the ROC curve, a common metric for comparing models in terms of how well they separate the positive and negative classes over the entire interval $p \in [0, 1]$. All of the models in this table are "good,"

Table 2
Numerics of Model Outputs of p. Table accompanies §2.5.2

	AdaBoost	Bal Bag	Bal RF	Easy Ens	Keras	Log Reg	RF	RUSBoost
n	713,566	713,566	713,566	713,566	713,566	713,566	713,566	713,566
p unique	705,474	270	3,999	3,015	694,949	706,940	458,530	706,938
Top 10	104	706,118	127,761	67,307	103	101	839	101
Top 100	404	713,239	662,937	294,986	423	392	5,872	392
min(p)	0.486	0.0	0.0	0.437	0.0	0.004	0.11	0.4990
max(p)	0.5066	1.0	1.0	0.592	0.996	0.91	0.31	0.5011
ROC AUC	0.753	0.763	0.801	0.730	0.778	0.735	0.708	0.754

with the Balanced Random Forest best and Random Forest worst, but the differences we are interested in are in a small intervals of p that satisfy the budgetary decision criteria, so the AUC will not be the primary metric we use.

2.5.3. Splitting p into Bands

The goal is to split the values of p into the smallest possible bands such that the target metrics are monotonic (increasing or decreasing) functions of the bands of p. As p increases, as we go from one band of p to the next we want TP/(FP + TP) and Pos/(Neg + Pos) to increase and FP/(FN + TP) to decrease, which they will do if the bands are large enough, but if the bands are too small the randomness and numerics will distort the results.

We tried two ways to split p into bands. The first was to cut it into bands of fixed width δ, but that posed several problems getting enough samples in each band to overcome the randomness while having small enough δ to give numerical precision to our choice of θ. It also would have required choosing a different δ for each model algorithm.

The method we chose was to vary the width of the bands based on the number of elements in the band and not splitting samples with the same value of p across two bands. We sorted the samples by decreasing p and, starting at the maximum value of p, went down the list until we had at least one thousand Neg samples and at least one thousand Pos samples in the band, then continued until we reached a different value of p. This method accommodated the Balanced Bagging results having most p rounded to one decimal place, giving eleven bands of p, while also slicing the $p \in [0.4990, 0.5011]$ of the RUSBoost results into 107 intervals with at least 1000 elements of each of the negative and positive classes.

The choice of 1000 for the minimum number of elements of the negative and positive classes was somewhat arbitrary, and more sophisticated methods could find an optimal size, an opportunity for future research (§5).

2.5.4. Understanding the Metrics in Bands of Values of p

In Table 3 we have various metrics as a function of p returned by the Balanced Forest Classifier. When choosing the best model for each metric we will use p-intervals of width 0.01, but for illustration purposes here we use intervals of width 0.05.

The "Neg" and "Pos" are the number of elements of each class in that interval of p. The Pos/(Neg + Pos) is one of our target metrics. The True Negatives (TN) are a running sum of Neg, and the False Positives (FP) are N − TN. Similarly, the False Negatives (FN) are a running sum of Pos, and the True Positives (TP) are P − FN. Precision, one of our target metrics is TP/(FP + TP), is the proportion of ambulances immediately dispatched that are needed. Recall, TP/(FN + TP), is the proportion of needed ambulances that are immediately dispatched. The last of our target metrics, FP/P, is the proportional increase in the number of ambulances sent (immediately or upon call from an eyewitness) when we automatically dispatch some ambulances based on an automated notification from a cell phone.

For example, if we set $\theta = 0.50$, then out of $n = 713,566$ automated crash notifications from cell phones, of the $P = 107,956$ that need an ambulance, we will send TP $= 77,763$ immediately and send the other FN $= 30,193$ after hearing from an eyewitness that an ambulance is needed. Additionally, we will send FP $= 163,691$ ambulances to crash persons who do not need one. Of the ambulances we immediately dispatched, Precision $= 32\%$ of them were needed, and of the crash persons who needed an ambulance, we immediately dispatched ambulances to Recall $= 72\%$ of them. The FP $= 163,691$ unnecessarily sent ambulances represent a FP/P $= 152\%$ increase in the number of ambulances sent to those crash persons with automated crash notifications, an increase over just ignoring the automated notifications and always waiting for a call from an eyewitness.

Table 3
Various Metrics as a Function of p returned by the Balanced Random Forest Classifier on the Hard Features. Table accompanies §2.5.4

p	Neg	Pos	$\frac{\text{Pos}}{\text{Neg+Pos}}$	TN	FP	FN	TP	Prec	Rec	$\frac{\text{FP}}{\text{P}}$
0.00	188,067	5,119	0.0265	188,067	417,543	5,119	102,837	0.1976	0.9526	3.8677
0.28	105,036	6,814	0.0609	293,103	312,507	11,933	96,023	0.2351	0.8895	2.8948
0.37	68,460	6,661	0.0887	361,563	244,047	18,594	89,362	0.268	0.8278	2.2606
0.43	52,376	6,894	0.1163	413,939	191,671	25,488	82,468	0.3008	0.7639	1.7755
0.48	38,235	6,464	0.1446	452,174	153,436	31,952	76,004	0.3313	0.7040	1.4213
0.52	33,681	7,045	0.1730	485,855	119,755	38,997	68,959	0.3654	0.6388	1.1093
0.56	28,986	7,597	0.2077	514,841	90,769	46,594	61,362	0.4034	0.5684	0.8408
0.60	24,231	7,849	0.2447	539,072	66,538	54,443	53,513	0.4458	0.4957	0.6163
0.64	19,354	7,996	0.2924	558,426	47,184	62,439	45,517	0.491	0.4216	0.4371
0.68	14,740	7,538	0.3384	573,166	32,444	69,977	37,979	0.5393	0.3518	0.3005
0.72	10,812	7,358	0.4050	583,978	21,632	77,335	30,621	0.586	0.2836	0.2004
0.76	7,896	6,939	0.4677	591,874	13,736	84,274	23,682	0.6329	0.2194	0.1272
0.80	6,710	8,163	0.5488	598,584	7,026	92,437	15,519	0.6884	0.1438	0.0651
0.85	7,026	15,519	0.6884	605,610	0	107,956	0	nan	0	0

If we were to move from $\theta = 0.50$ to $\theta = 0.55$, then we would immediately dispatch far fewer (Neg + Pos = $43,098 + 8,652 = 51,750$) ambulances. Pos = $8,652$, or Pos/(Neg + Pos) = 17% of the ambulances we decided to not send because we moved from $\theta = 0.50$ to $\theta = 0.55$, were needed. In that band of θ, automated calls from cell phones have a 17% chance of needing an ambulance.

2.5.5. *Choosing Values of θ for each Budgetary Decision Metric*

Using the Balanced Random Forest Classifier trained on the Hard features as an example, from the data in Table 3 we can find the decision thresholds θ that satisfy each of our three political decision criteria. In the table, $\frac{\text{FP}}{\text{P}} = 0.05$ somewhere in the interval $p \in [0.85, 0.90)$. Zooming in on that interval in Table 4, we see that if we wanted to satisfy that criterion, we would choose $\theta = 0.86$ as our decision threshold. In the table we can also see the marginal effects on FP/P of choosing a slightly larger or smaller θ instead.

Similarly, for our second political criterion Precision $= \frac{\text{TP}}{\text{FP+TP}} = \frac{2}{3}$, we would choose $\theta = 0.81$ as our decision threshold, and for marginal probability, $\frac{\text{Pos}}{\text{Neg+Pos}} = 0.50$, we would choose $\theta = 0.79$.

We cannot get more detailed values of θ for the Balanced Random Forest Classifier because almost all of the values of p in the model output are rounded to two decimal places. For all of our models, though, we would be stretching our credibility to give more precise answers because we just do not have enough data to give our criteria as monotonic functions of p over much smaller intervals of p.

Table 4
Various Metrics as a Function of *p*, in more detail. Table accompanies §2.5.5

p	Neg	Pos	$\frac{\text{Pos}}{\text{Neg+Pos}}$	TN	FP	FN	TP	Prec	Rec	$\frac{\text{FP}}{\text{P}}$
0.75	2,495	1,804	0.42	583,902	21,708	77,268	30,688	0.59	0.28	0.20
0.76	2,259	1,721	0.43	586,161	19,449	78,989	28,967	0.60	0.27	0.18
0.77	2,041	1,779	0.47	588,202	17,408	80,768	27,188	0.61	0.25	0.16
0.78	1,882	1,817	0.49	590,084	15,526	82,585	25,371	0.62	0.24	0.14
0.79	1,805	1,706	0.49	591,889	13,721	84,291	23,665	0.63	0.22	0.13
0.80	1,604	1,675	0.51	593,493	12,117	85,966	21,990	0.64	0.20	0.11
0.81	1,440	1,585	0.52	594,933	10,677	87,551	20,405	0.66	0.19	0.10
0.82	1,321	1,697	0.56	596,254	9,356	89,248	18,708	0.67	0.17	0.09
0.83	1,162	1,639	0.59	597,416	8,194	90,887	17,069	0.68	0.16	0.08
0.84	1,171	1,566	0.57	598,587	7,023	92,453	15,503	0.69	0.14	0.07
0.85	970	1,548	0.61	599,557	6,053	94,001	13,955	0.70	0.13	0.06
0.86	938	1,508	0.62	600,495	5,115	95,509	12,447	0.71	0.12	0.05
0.87	784	1,475	0.65	601,279	4,331	96,984	10,972	0.72	0.10	0.04
0.88	764	1,367	0.64	602,043	3,567	98,351	9,605	0.73	0.09	0.03
0.89	695	1,383	0.67	602,738	2,872	99,734	8,222	0.74	0.08	0.03
0.90	559	1,318	0.70	603,297	2,313	101,052	6,904	0.75	0.06	0.02

2.5.6. *Choosing the Best Model for each Budgetary Decision Metric*

For each budgetary constraint we want to find the model that, within the constraint, will immediately dispatch the most ambulances to crash persons who need them (TP). Using as an example our first budgetary constraint, FP/P = 0.05, we need to find, for each model, each set of hyperparameters for the model, and each transformation of the *p* outputs, whether there exists a neighborhood of *p* where FP/P is close to 0.05, then find the best θ interval in that neighborhood. Of those valid results, find the model that gives the most TP.

Table 5 shows the best results for each model algorithm. Within these, the Balanced Random Forest Classifier gives the best results, sending more needed ambulances while staying within the budgetary constraint. The KerasClassifier with the Binary Focal Crossentropy loss function is a close second, and those two are clearly better than the other six models.

Table 5
Comparing Models: Best results for each model for budgetary criterion FP/P closest to 0.05. Table accompanies §2.5.6

Algorithm	Features	α	γ	Trans	p	Neg	Pos	FP/P	TP
Bal RF	Hard	0.50	0	None	0.86	938	1,508	0.047	12,447
Keras	Hard	0.50	2.0	100	0.58	1,264	1,556	0.054	11,287
RUSBoost	Hard	0	0	100	0.71	1,245	1,200	0.054	7,336
Log Reg	Hard	0.50	0	95	0.81	348	393	0.051	7,278
AdaBoost	Hard	0	0	98	0.83	768	735	0.053	7,097
Bal Bag	Hard	0	0	None	0.9	8,548	10,487	0.03	6,610
RF	Hard	0	0	100	0.74	923	673	0.051	5,909
Easy Ens	Hard	0	0	100	0.72	2,378	2,296	0.048	5,306

3. Results

3.1. Data and Image Files

The results in tables 6, 7, and 8 are selections from the `FP_P_0_05.csv`, `Prec_0_667.csv`, and `mProb_0_5.csv` files in the `./Keras/Analyze_Proba` folder at `www.github.com/bburkman/Ambulance_Dispatch`

Each row of each of those three files represents a different combination of algorithm, hyperparameters, features and transformation; for instance the `LogReg_5_Fold_alpha_0_5_Easy_Test_Transformed_98` is the logistic regression algorithm with $\alpha = 0.5$ on the Easy features transformed with 0.01 quantile $\rightarrow$ 0 and 0.99 quantile $\rightarrow$ 1.0.

Each row of `FP_P_0_05.csv` gives, for that (algorithm, hyperparameter, feature, transformation) combination the value of p where, on $[p, p + 0.01)$, the value of FP/P is closest to 0.05, along with other metrics at that p-interval. Similarly, the other files give metrics at the p-interval where precision is closest to 0.667 and marginal probability is closest to 0.5.

For more details on the results of each (algorithm, hyperparameters, features, transformation) combination for all hundred intervals of $[p, p + 0.01)$, see, for example,
`LogReg_5_Fold_alpha_0_5_Easy_Test_Transformed_98_100.csv`. Most of those data files also come in a `.tex` version in the same directory.

The area under the ROC curve for each of the 13 models on each of the three sets of data features is given in `ROC_AUC.csv`.

The plots for the model output are in the `./Keras/Images` folder. For each model on each set of data features there are five images, for instance,
`BRFC_alpha_0_5_Easy_Pred`,
`BRFC_alpha_0_5_Easy_Test_Pred_Wide`, and
`BRFC_alpha_0_5_Easy_Pred_Zoom`,
`BRFC_alpha_0_5_Easy_Test_Pred_Zoom_Wide`, and
`BRFC_alpha_0_5_Easy_Test_ROC`,
and each image comes in a `.png` and `.pgf` version. The `Wide` pictures are 4.5 inches wide, and the others 2.0 inches. The first two images have a domain of $p \in [0, 1]$, and the `Zoom` images from the minimum to maximum values of p.

3.2. Easy, Medium, and Hard Features

Figure 10 shows the raw model output and ROC curves for the Balanced Random Forest Classifier model trained on the Easy, Medium, and Hard feature sets. All three have significant overlap of the negative (does not need an ambulance) and positive (needs an ambulance) classes, but comparing the Hard to the Easy, the negative class in the Hard is pushed to the left and the positive to the right, better separating the two classes and giving a space (up to about $p = 0.8$) to choose a decision threshold θ that will send more needed than unneeded ambulances.

The ROC (Receiver Operating Characteristic) curves illustrate how well the models separate the positive and negative classes, with area under the curve (AUC) of 0.5 being no better than random and 1.0 being perfect separation. The ROC AUC also support the idea that the models built on the Hard features set are much more predictive than the Medium, which are better than the Easy.

The thirteen models built on the Easy feature set had AUC in $[0.552, 0.665]$, Medium in $[0.640, 0.729]$, and Hard in $[0.708, 0.801]$. If we take out the worst Hard model and the worst Medium model, the ranges do not overlap.

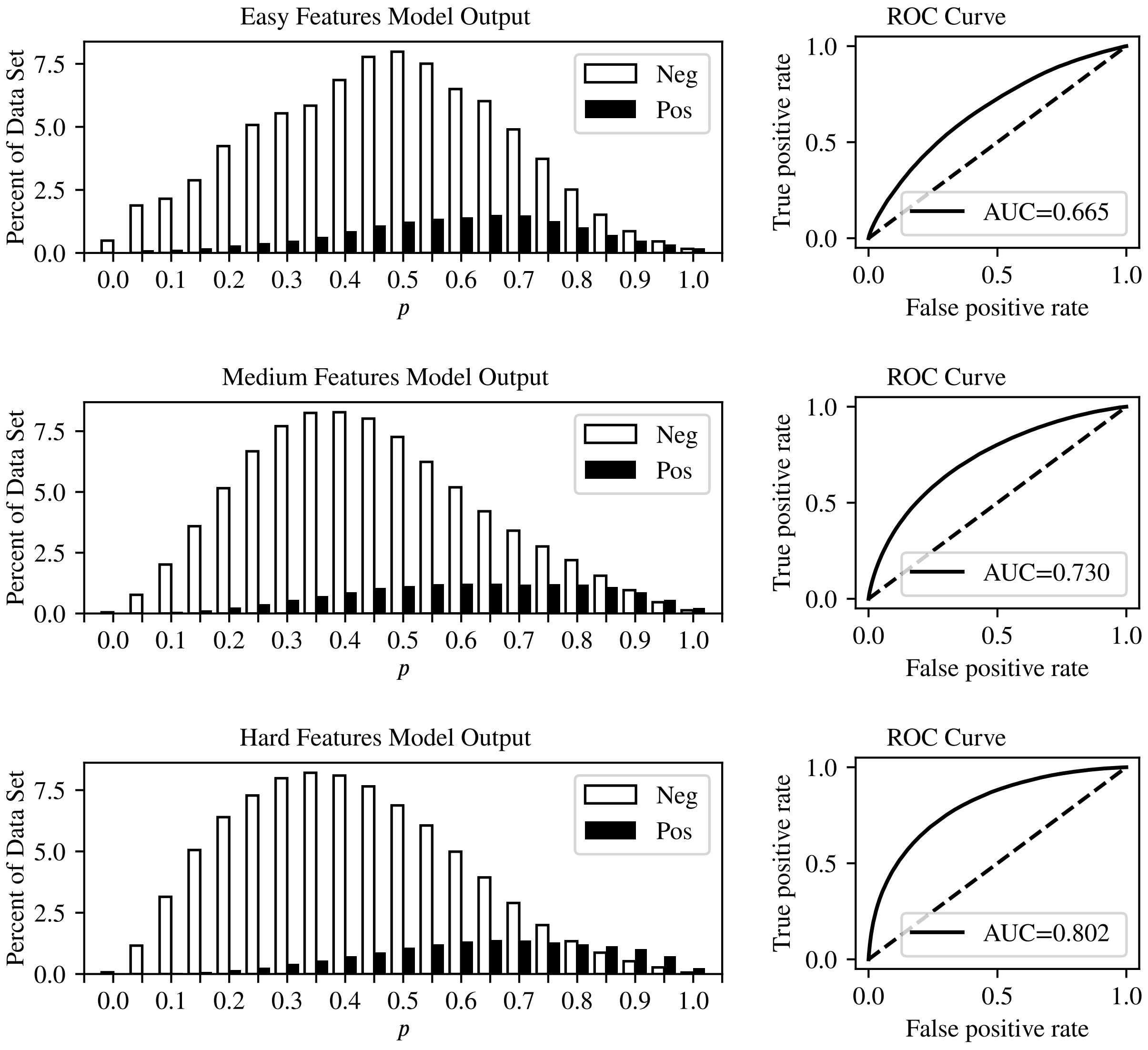


Figure 10: Balanced Random Forest Classifier with $\alpha = 0.5$ Model Results for Different Sets of Data Features. Figure accompanies §3.2

3.3. Best Model for Each Budgetary Criterion and Feature Set

Our first budgetary decision criterion was that the increase in number of ambulances sent to crash persons with automated notifications from cell phones should be not more than 5%. Table 6 gives, for each feature set (Easy, Medium, Hard) the best models, with "best" meaning that the model recommends sending the most ambulances that are actually needed (TP) subject to the constraint that we choose our decision threshold θ to be the value of p such that FP/P is closest to 0.05 on the interval $[p, p + 0.01)$,

In Table 6 we have included the best three models for each set of data features, "best" in that those models immediately dispatch the most needed ambulances (TP) while keeping within the budgetary constraint FP/P ≈ 0.05.

Table 6
Best models and transformations for FP/P = 0.05 for each algorithm. Table accompanies §3.3

Algorithm	Features	α	γ	Trans	p	Neg	Pos	FP/P	TP
Bal RF	Easy	0.50		98	0.93	997	564	0.052	4,270
Bal Bag	Easy			95	0.97	755	389	0.056	4,197
Keras	Easy	0.85	0.0	None	0.75	2,345	1,106	0.058	3,469
Bal RF	Medium	0.50	0	95	0.94	679	523	0.055	7,290
Keras	Medium	0.50	2.0	100	0.69	1,328	1,134	0.055	6,595
AdaBoost	Medium	0	0	100	0.74	1,114	992	0.053	5,699
Bal RF	Hard	0.50	0	None	0.86	938	1,508	0.047	12,447
Keras	Hard	0.50	2.0	100	0.58	1,264	1,556	0.054	11,287
RUSBoost	Hard	0	0	100	0.71	1,245	1,200	0.054	7,336

Table 7
Best models and transformations for Precision = TP/(FP + TP) = 2/3 for each algorithm. Table accompanies §3.3

Algorithm	Features	α	γ	Trans	p	Neg	Pos	Prec	TP
Bal RF	Easy	0.5		98	0.99	430	343	0.507	1,411
Bal Bag	Easy			None	0.99	220	191	0.49	835
Keras	Easy	0.5	2.0	None	0.51	102	43	0.497	79
Bal RF	Medium	0.5		98	0.99	347	557	0.65	1554
Keras	Medium	0.5	0.0	None	0.73	51	55	0.664	326
Log Reg	Medium	0.5	0.0	100	0.83	25	22	0.623	114
Bal RF	Hard	0.5		None	0.82	1,321	1,697	0.667	18,708
Keras	Hard	0.5	2.0	95	0.85	617	769	0.666	10,701
Log Reg	Hard	0.5		None	0.69	144	235	0.666	2,269

We have not here included similar results, like the Balanced Random Forest model with different hyperparameters, because the differences between the results of very similar models is more about the numerics and randomness than predictive of what a similar model on a slightly different dataset with different random seeds would produce.

Our second budgetary decision criterion was that, of the ambulances immediately dispatched, at least 2/3 should be actually needed. Table 7 gives, for each feature set (Easy, Medium, Hard) the best models, with "best" meaning that the model recommends sending the most ambulances that are actually needed (TP) subject to the constraint that we choose our decision threshold θ to be the value of p such that Precision = TP/(FP + TP) is closest to 0.667 on the interval $[p, p + 0.01)$.

Note that in the Easy features in Table 7, none of the models attain Precision = TP/(FP + TP) close to 2/3. A city wanting to build a recommendation system on the Easy features would need to be satisfied with Precision ≈ 0.5, that only half of the ambulances immediately dispatched would be needed.

Our third budgetary decision criterion was that each ambulance immediately dispatched should have at least a 50% chance of being needed. Table 8 gives, for each feature set (Easy, Medium, Hard) the best models, with "best" meaning that the model recommends sending the most ambulances that are actually needed (TP) subject to the constraint that we choose our decision threshold θ to be the value of p such that mProb = Pos/(Neg + Pos) is closest to 0.50 on the interval $[p, p + 0.01)$.

Table 8
Best models and transformations for mProb = Pos/(Neg + Pos) ≈ 0.5 for each algorithm. Table accompanies §3.3

Algorithm	Features	α	γ	Trans	p	Neg	Pos	mProb	TP
Bal RF	Easy	0.5	0	None	0.98	228	228	0.5	395
AdaBoost	Easy	0	0	100	0.93	244	167	0.406	169
Log Reg	Easy	0.5	0	100	0.87	81	62	0.434	147
Bal RF	Medium	0.5	0	95	0.93	1,211	1,191	0.496	7,813
Keras	Medium	0.5	1.0	90	0.97	444	457	0.507	6,521
Easy Ens	Medium	0	0	98	0.91	812	800	0.496	5,259
Bal RF	Hard	0.5	0	None	0.78	1,882	1,817	0.491	25,371
Bal Bag	Hard	0	0	None	0.85	97	86	0.47	17,160
Keras	Hard	0.5	2.0	95	0.78	1,104	1,099	0.499	16,869

4. Conclusions and Discussion

Choosing a tradeoff between saving lives and saving money is a political decision, but the decision can be informed with models showing the likely outcomes of the possible choices.

Many cell phones can automatically notify the emergency dispatcher when they detect the deceleration profile of a crash. The dispatcher will immediately send police to investigate, but should they also immediately dispatch an ambulance, which has about a 15% chance of being needed, or wait for a call from an eyewitness? We have explored options for an AI recommendation system that would take the known information about the crash, a model built on historical crash data, and a decision criterion chosen by the political decision makers, and return a recommendation for whether to immediately dispatch an ambulance or to wait.

The main problem with such a recommendation system is that it will recommend sending some ambulances that are not needed. Budgets are limited, and priorities have to be chosen. We showed how to incorporate three kinds of decision criterion: Percent increase in number of ambulance calls, percent of immediately dispatched ambulances actually needed, and minimum probability that each immediately dispatched ambulance is needed.

We considered many challenges, including the randomness inherent in machine learning models and how the numerics severely limit the precision we can claim in our results. The most significant challenge we considered was the input data required to make a useful recommendation system. We considered three sets of input features that we called Easy, Medium, and Hard, but that can also be thought of as Free, Expensive, and Problematic.

Even through the randomness and numerics, the results show that the results of models built on the Hard features are clearly better than those built on the Medium features, which are clearly better than those built on the Easy features. The models built on the Easy features, however, are still better than random guessing, and a recommendation system built on just those features may be worth the expense, especially since the emergency dispatcher already has that information.

5. Simplifying Assumptions and Opportunities for Future Research

All models are simplifications, and we should acknowledge the most egregious of our simplifying assumptions. Some of the simplifying assumptions may hint at opportunities for future research.

Section	Simplifying Assumption
§2.1	All ambulances sent based on calls from eyewitnesses are actually needed. All automated crash notifications from cell phones refer to an actual crash, not just hard braking, *i.e.* the notifications have no false positives.
§2.2	The class ratio (P/N) in the automated crash notification from cell phones will be close to that in the CRSS data, $1/5$.
§2.2	The crash persons in the CRSS data are representative of the future crash persons whose cell phones send a crash notification. (Several layers to unpack here)
§2.3	The data features we seek for each automated crash notification will be available and accurate.

Section	Opportunities for Future Research
§2.2	Find data on crashes that spawned an automated notification from a cell phone.
§2.3	We tested only three sets of features and did not test to see which features or combinations of features were most useful in predicting needing an ambulance.
§2.5.3	Find a better way to slice the p-values into intervals such that the target metrics are monotonic functions of the intervals.
§2.4.2	We found that varying the hyperparameters for class weight and focal loss did not significantly vary the ROC AUC, a measure of how well the model separates the positive and negative classes over the whole range $p \in [0, 1]$. Do those hyperparameters make a difference in how well the model separates the positive and negative classes on the right tail of the p distribution, the part relevant to our work?

Funding Statement

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Conflict of Interest

Declarations of interest: none

Acknowledgements

George Broussard contributed to this work in the NSF Research Experiences for Undergraduates program.

Data Availability

The CRSS data is publicly available at
`https://www.nhtsa.gov/crash-data-systems/crash-report-sampling-system`
All of the code and generated data, tables, and graphs are available at `http://www.github.com/bburkman/Ambulance_Dispatch`

CRediT authorship contribution statement

J. Bradford Burkman: Conceptualization, Investigation, Writing - original draft, Visualization. **Chee-Hung Henry Chu:** Supervision, Methodology, Writing - review and editing. **Miao Jin:** Supervision, Methodology. **Malek Abuhijleh:** Data curation, Investigation, Methodology. **Xiaoduan Sun:** Data curation, Writing - review and editing.

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