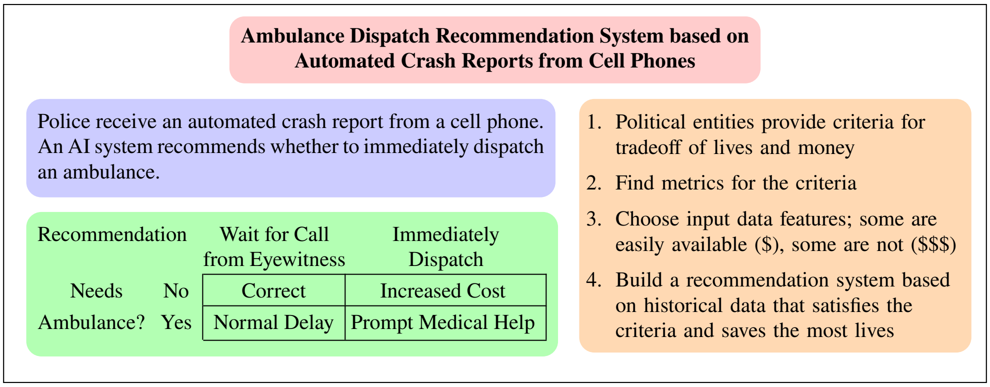
# Graphical Abstract

## 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 Ambulance? | No | Correct | Increased Cost |
| | 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

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

- 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

J. Bradford Burkman[a,b,*,1], Chee-Hung Henry Chu[a], Miao Jin[a], Malek Abuhijleh[a,c] and Xiaoduan Sun[c]

[a]School of Computing and Informatics, University of Louisiana at Lafayette, 301 E. Lewis St, Lafayette LA, 70503, USA
[b]Louisiana School for Math, Science, and the Arts, 715 University Pkwy, Natchitoches LA, 71457, USA
[c]Department of Civil Engineering, University of Louisiana at Lafayette, 131 Rex St, Lafayette LA, 70504, USA

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 $\theta$, 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 $\theta$ 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 $\theta$ 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 $\theta$ 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.]

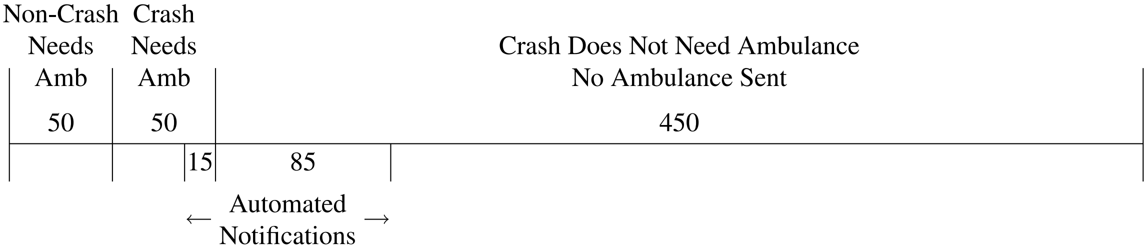

Non-Crash Needs Amb
Crash Needs Amb
Crash Does Not Need Ambulance No Ambulance Sent
50
50
450
15
85
← Automated Notifications →

**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.

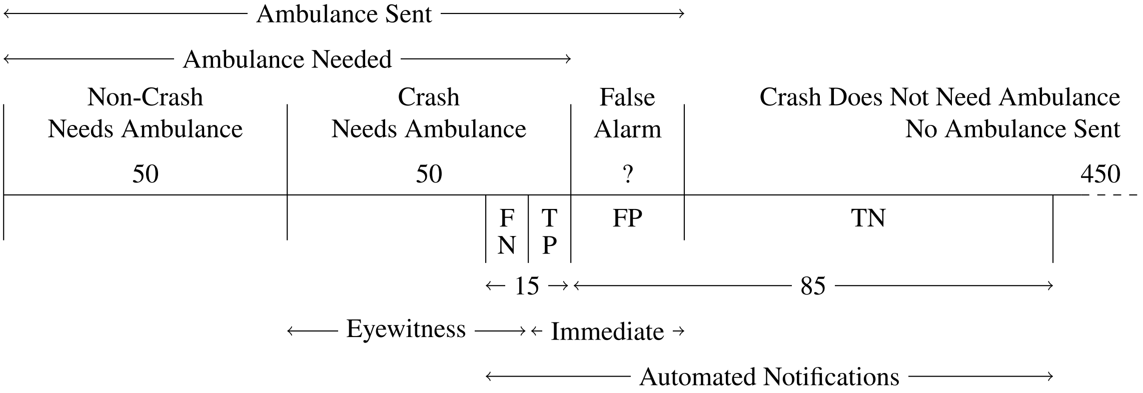


**Figure 2:** Springfield after implementing immediate dispatch of ambulances. Figure accompanies §1.1

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 Ambulance? | No | Correct | Increased Cost |
| | 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 $\theta$ 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 $\theta$, Springfield would immediately dispatch ambulances to all of the crashes with a $p$ value to the right of $\theta$. The Pos (Needs ambulance) to the right of $\theta$ would get more prompt medical attention (TP), but the Neg (Does not need ambulance) to the right of $\theta$ would be wasted ambulance runs (FP) . At $\theta = 0.8$, TP and FP are about equal, but as we consider smaller $\theta$ the number of TP increases by smaller and smaller amounts while the number of FP grows dramatically.

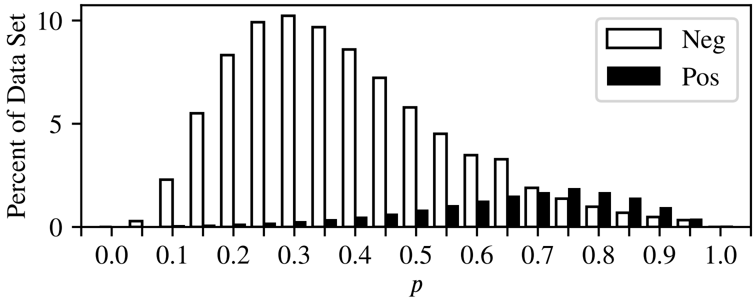


**Figure 4:** Example model test results. Figure accompanies §1.1

We will consider three ways the leaders of Springfield can think about how to choose $\theta$, 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 from the US National Highway Traffic Safety Administration (NHTSA), and looked at the data at the level of a person involved in a crash ("crash person") for a total of 713,566 samples. In §2.2 we describe the benefits and limitations of this dataset. The dataset has imputed missing values for some, but not all, of the features we wanted to use, so, in ways that we have not seen in the literature, we recreated the method used by the authors of the dataset to impute missing values (IVEware) and compared it against other methods, deciding on a round-robin random forest method. We briefly describe other aspects of the preprocessing, including binning and engineering features, but interested readers can get full details by reading the code.

Some data features are easily available, like the weather and time of day, but some would be challenging (expensive) to have available in real time, and having some available in real time would pose privacy and data security concerns, so we investigated three levels of data availability that we will call Easy, Medium, and Hard, but one can also think of as Free, Expensive, and Problematic. We describe the three levels of data in §2.3 and compare the results in §3.

We used eight supervised learning binary classification algorithms with a variety of hyperparameters, for a total of thirteen models. Binary classification algorithms return, for each sample (crash person, feature vector), a value $p \in [0, 1]$ that increases with the probability that the crash person needs an ambulance, and we have for each sample in the training data set a value $y \in \{0, 1\}$ that tells us whether the crash person actually needed an ambulance. The eight algorithms returned different shapes of output, which we explore in §2.4.1.

The results themselves do not tell us whether we should immediately dispatch an ambulance. We need to choose, for each model, a decision threshold $\theta$ such that if for a new automated crash report $p > \theta$, then the system recommends immediately dispatching an ambulance. The criteria for the decision threshold are political, not technical, decisions, and in §2.1 we posit three budgetary criteria: Capping the percentage increase in ambulances sent to crashes with automated notifications (increase because of false alarms), setting a floor under the percentage of ambulances immediately dispatched that are actually needed (precision), and setting a minimum likelihood that the last ambulance sent is actually needed. For each criterion have created a metric to determine the decision threshold on the $p$. 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. For each criterion we compared results of different models and sets of features using the simple measure of, at the decision threshold, which model immediately dispatches the largest number of needed ambulances (TP, which is proportional to the recall).

We found that the first criterion metric is a nondecreasing function of $p$, so choosing a decision threshold is straightforward, but the second and third criterions' metric are generally decreasing, but not at a finely granular level. In §2.5.1 we consider some methods for smoothing the results to choose the decision threshold. Models built on the Easy features do not do nearly as good a job at separating the negative and positive classes as do the models built on the Medium features, which do give worse results than models built on the Hard features, and in §3 we quantify how much worse (in terms of false alarms) for each model and feature set, but for some metrics the Easy decision metric may exist only in the far tail of the distribution, too far out to be actionable. Since the cost of having the Medium or Hard features available may be mostly a fixed cost, and the number of false positives recommended by the system is proportional to the size of the city or region implementing the system, the economies of scale of such a recommendation system may be considerable.

To support transferability, we have used a public dataset and made public all of the code we used in our investigation with 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

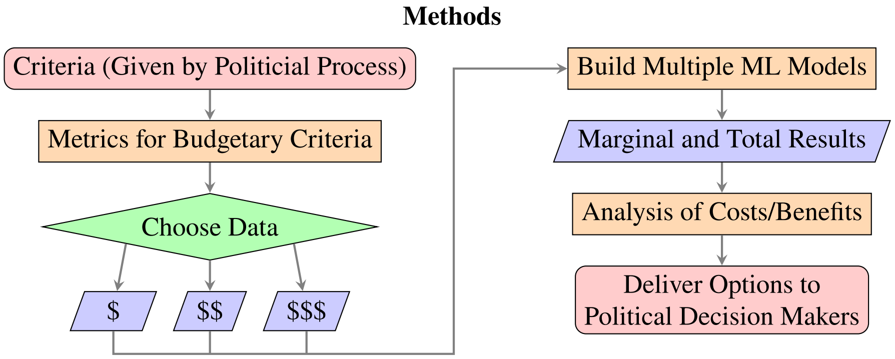

Methods
Criteria (Given by Politicial Process)
Metrics for Budgetary Criteria
Choose Data
$
$$
$$$
Build Multiple ML Models
Marginal and Total Results
Analysis of Costs/Benefits
Deliver Options to Political Decision Makers

**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.

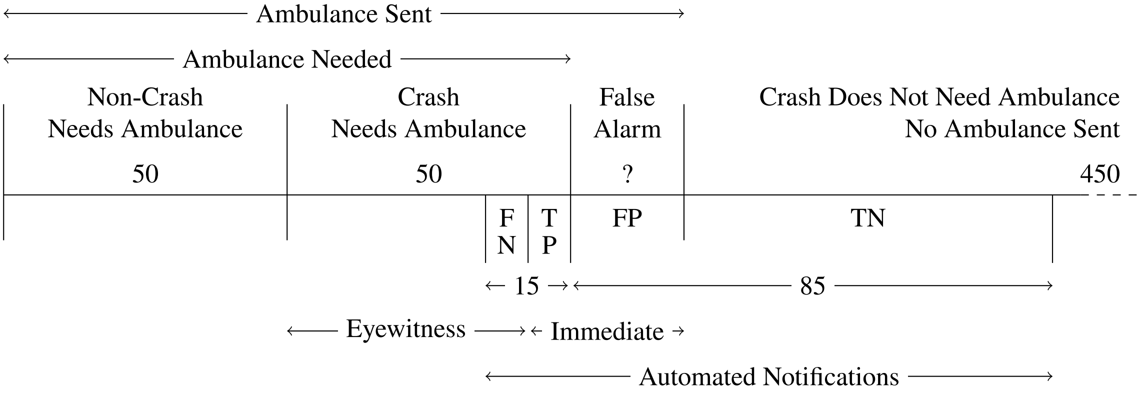


**Figure 6:** Springfield after implementing immediate dispatch of ambulances. Figure accompanies §1.1

### 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 $\theta$ where the number of false positives is 5% of the positive class.

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

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 $\theta$ 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.

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

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.

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

## 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 $\alpha$ and one of which takes the focal loss parameter $\gamma$. (See Table 2.4.1) We learned models for various values of the

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

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

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 $\gamma = 2.0$.

### *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 hyperparameter $\alpha$ and a focal loss parameter $\gamma$. Varying these hyperparameters gave us different shapes of distributions of $p$, as shown in Figure 7, which also gives the ROC AUC for two runs of each model with different random seeds. That the model on the left has both the least and the greatest ROC AUC illustrates that, between models of the same algorithm with different class and focal weights, the effectiveness of the model in separating the positive and negative classes depends as much on the random seed as on the choice of weights.

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).

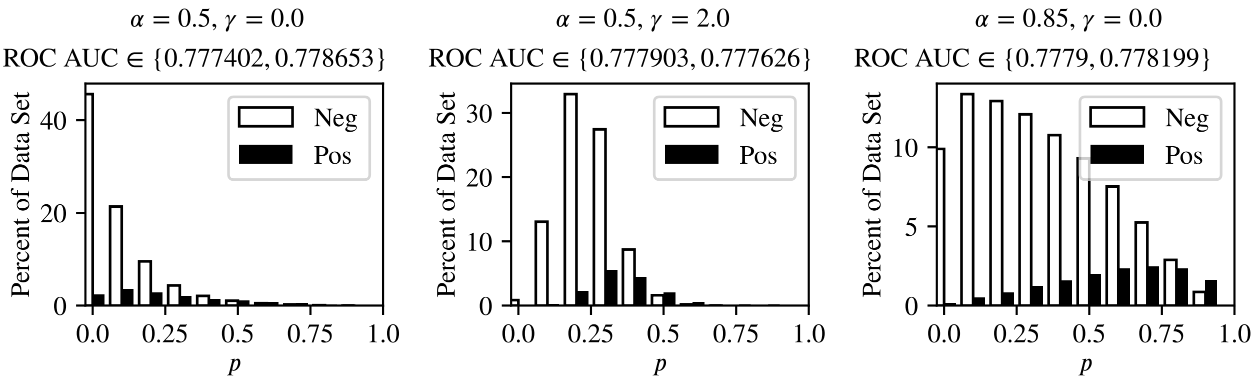


**Figure 7**: KerasClassifier with Different Hyperparameters with ROC AUC for Two Model Runs with Different Random Seeds. Figure accompanies §2.4.2

### *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 $\theta$. 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.

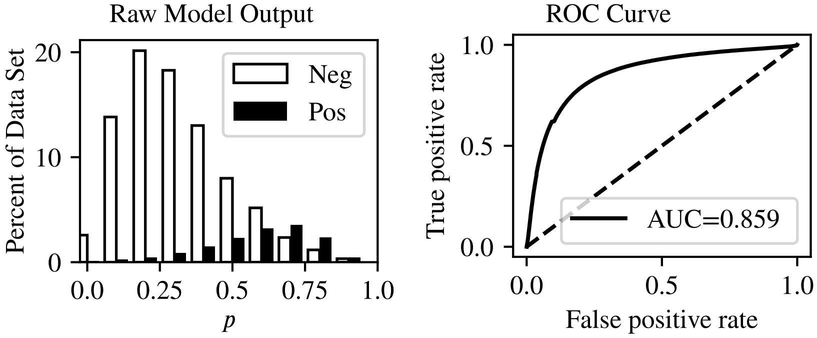
### *2.4.4. Interpreting Supervised Learning Binary Classification Results*

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 $\theta$, 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.



Choosing decision threshold $\theta = 0.5$:

| | | Prediction | |
|---|---|---|---|
| | | N | P |
| Actual | 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

### 2.4.5. *Comparing Outputs of Different Models*

The eight model algorithms not only give different results, but different kinds of results, and we have to find a way to compare them. Ideally, we will find ways to evaluate the results that will apply to all of the kinds of model output. 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.

To give appropriate results for Balanced Bagging with a $p$ range of width 1.0 and RUSBoost with a range of width 0.002, we built into the code a variable for numerical precision that depends on the range of $p$ for that model, num_prec $= -\lceil \log_{10}(\max(p) - \min(p)) \rceil$, to which we can then add the number of digits appropriate for the purpose.

The numerics in the model results are also different. Most of the models give, for the 713,566 samples, at least 100,000 unique values of $p \in [0, 1]$, making the discrete results nearly continuous. The AdaBoost, KerasClassifier, Logistic Regression, and RUSBoost algorithms are fairly consistent with about 140,000 unique values of $p$ for results on the Easy features, 640,000 for the results on the Medium features, and 700,000 on the Hard features. The Random Forest classifier gives about half as many unique results, but proportionally for the three features sets.

The outliers in the numerics are the Balanced Random Forest, Balanced Bagging, and Easy Ensemble. The Balanced Random Forest method on the Hard features gives less than 4,000 unique values of $p$ on the Hard features because 93% of its $p$ values are rounded to two decimal places. The Balanced Bagging results on the Hard features have less than 300 unique values because 99% of its $p$ values are rounded to one decimal place. While the other algorithms had fewer unique values for the Medium features and far fewer for the Easy, the Balanced Random Forest and Balanced Bagging have more for the Medium and far more for the Easy, with the number of unique Easy results being comparable to those of the other algorithms. The Easy Ensemble results for all three features sets have about 50% of the results rounded to two decimal places. For full details see `Analyze_Proba/Value_Counts_y_proba.csv`.

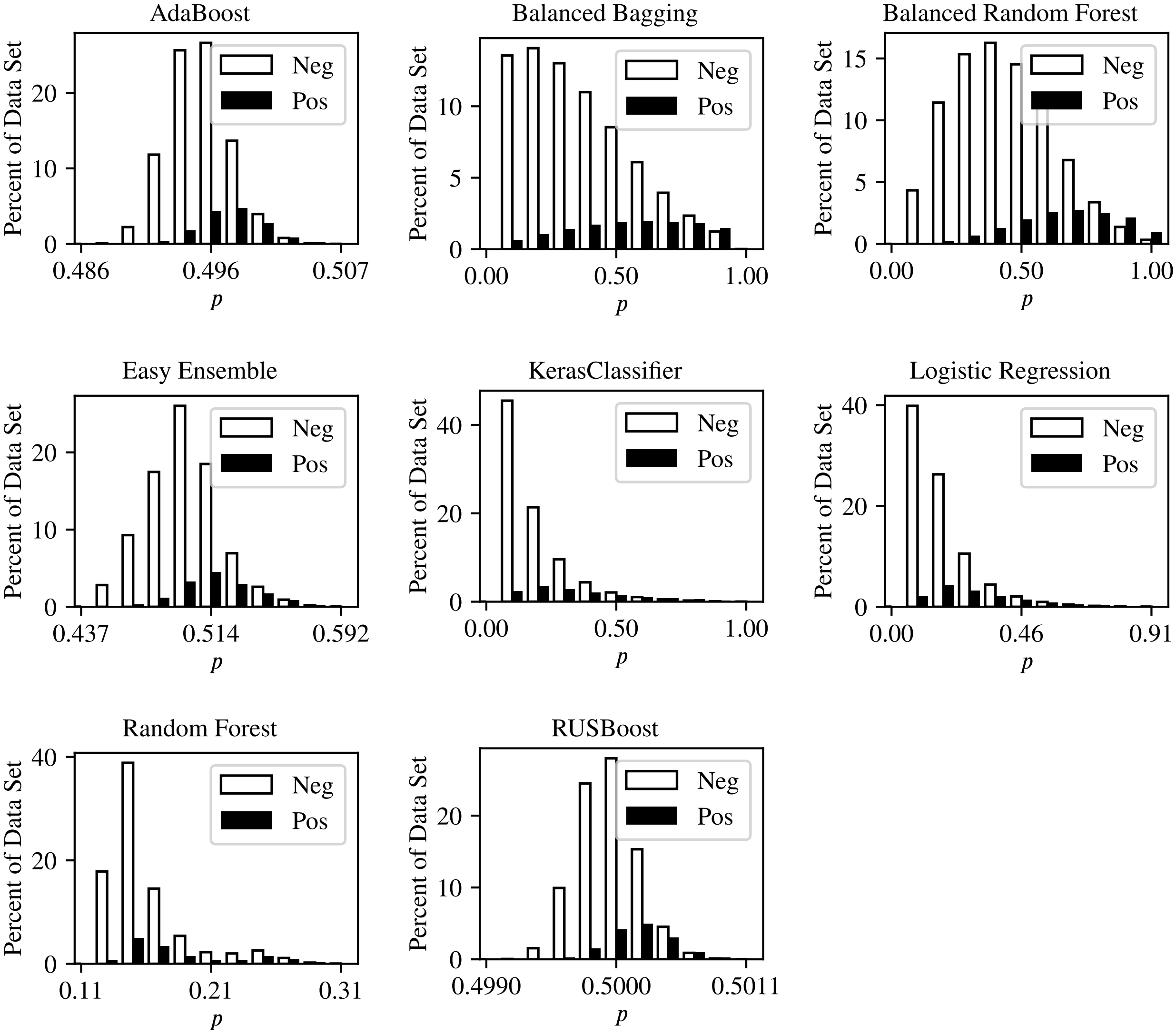


**Figure 9:** Raw Model Outputs. Figure accompanies §2.4.5

## 2.5. Interpreting Model Results

### 2.5.1. Finding $\theta$ for Each Budgetary Decision Metric

For each budgetary metric and each model we need to find a corresponding decision threshold $\theta$. For each new crash notification the model will output a prediction value $p$, and if $p \geq \theta$ the system will recommend immediately dispatching an ambulance.

For each of the 713,566 samples we use from the CRSS dataset we have a target value $y \in \{0, 1\}$ that tells whether the sample is in the Neg or Pos class. Each model returns for each of those historical samples a value $p \in [0, 1]$ that indicates whether the model predicts that the sample is in the positive and negative class. For each model we need to find the value of $p$ that corresponds to each of the budgetary decision criteria to set as the decision threshold $\theta$.

To illustrate our methods for finding $\theta$ for each budgetary decision metric and each model we will use the results of the Random Forest Classifier on the hard features, which returns values $p \in [0.10619, 0.311074]$. Table 2 shows some of the results. We have rounded $p$ to four decimal places and sorted model results by increasing $p$, giving the number of elements of the negative and positive classes for each $p$. From Neg and Pos we can calculate the TN, FP, FN, and

**Table 2**
Metrics on $p$ Output of Random Forest Classifier on the Hard Features. Table accompanies §2.5.1

| $p$ | Neg | Pos | $\frac{\text{Pos}}{\text{Neg+Pos}}$ | TN | FP | FN | TP | Prec | FP/P |
|---|---|---|---|---|---|---|---|---|---|
| 0.1062 | 1 | 0 | 0 | 1 | 605,609 | 0 | 107,956 | 0.1513 | 5.6098 |
| 0.1063 | 86 | 2 | 0.0227 | 87 | 605,523 | 2 | 107,954 | 0.1513 | 5.609 |
| 0.1064 | 51 | 0 | 0 | 138 | 605,472 | 2 | 107,954 | 0.1513 | 5.6085 |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |
| 0.2579 | 33 | 40 | 0.5479 | 600,161 | 5,449 | 102,100 | 5,856 | 0.518 | 0.0505 |
| 0.258 | 39 | 26 | 0.4 | 600,200 | 5,410 | 102,126 | 5,830 | 0.5187 | 0.0501 |
| 0.2581 | 39 | 25 | 0.3906 | 600,239 | 5,371 | 102,151 | 5,805 | 0.5194 | 0.0498 |
| 0.2582 | 42 | 31 | 0.4247 | 600,281 | 5,329 | 102,182 | 5,774 | 0.52 | 0.0494 |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |
| 0.2858 | 4 | 8 | 0.6667 | 605,179 | 431 | 106,858 | 1,098 | 0.7181 | 0.004 |
| 0.2859 | 1 | 9 | 0.9 | 605,180 | 430 | 106,867 | 1,089 | 0.7169 | 0.004 |
| 0.286 | 4 | 11 | 0.7333 | 605,184 | 426 | 106,878 | 1,078 | 0.7168 | 0.0039 |
| 0.2861 | 1 | 10 | 0.9091 | 605,185 | 425 | 106,888 | 1,068 | 0.7153 | 0.0039 |
| 0.2862 | 5 | 6 | 0.5455 | 605,190 | 420 | 106,894 | 1,062 | 0.7166 | 0.0039 |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |
| 0.3097 | 0 | 1 | 1 | 605,610 | 0 | 107,953 | 3 | 1 | 0 |
| 0.3108 | 0 | 1 | 1 | 605,610 | 0 | 107,954 | 2 | 1 | 0 |
| 0.3111 | 0 | 2 | 1 | 605,610 | 0 | 107,956 | 0 | nan | 0 |

TP we would have if we chose $\theta$ to be that value of $p$. The number of negative and positive samples are constant at $N = 605,610$ and $P = 107,956$. TN is the cumulative sum of Neg, and FP = N − TN; similarly for FN and TP.

In Table 2, we have shown the results for four bands of $p$. The first and fourth are the beginning and end of the range of $p$. The second range shows where FP/P ≈ 0.05, the first budgetary decision metric. The third range illustrates that while Precision generally increases from 0.15 (the class ratio) to 1, it is not perfectly nondecreasing, even with $p$ rounded to four decimal places. Note in the fourth column, Pos/(Neg+Pos), (marginal probability), the values generally increase from 0 to 1 but not in a smooth way. We will have to significantly smooth that metric to find the value of $p$ where it equals 50%. The full table is at `Analyze_Proba/RFC_Hard_Run_0_Round_4_Rolling_Intervals`.

Our **first budgetary decision metric**, FP/P, is a nonincreasing function of $p$ because $P$ is constant and FP is P minus the cumulative sum of nonnegative integers Neg. Because FP/P is a nonincreasing function of $p$, we can choose $\theta$ to be the value of $p$ where FP/P is closest to 0.05. For this run of the Random Forest Classifier with the hard features we can choose $\theta = 0.2580$, and a second run with a different random seed gave $\theta = 0.2583$, so we can say with some confidence that we should choose $\theta = 0.258$ for this model.

Table 2 shows that our **second budgetary decision metric**, Precision = TP/(FP + TP), generally increases from 0.15 to 1 (0.15 is the class ratio P/(N + P)), but is not an increasing function of $p$ at that level of granularity.

To go from one $p$ to the next, or from one band of $p$ to the next,

$$\frac{\Delta \text{TP}}{\Delta p} = -\text{Neg} \qquad \text{and} \qquad \frac{\Delta \text{FP}}{\Delta p} = -\text{Pos} \tag{5}$$

For large changes in $p$, Prec($p$) is an increasing function, but what do we mean by "large"? There is a condition on our $p$-interval such that Prec($p$) will be an increasing function.

**Table 3**
Metrics on $p$ Output of Random Forest Classifier on the Hard Features with Minimum of 50 Elements of Each Class in Each Band. Table accompanies §2.5.1

| $p$ | Neg | Pos | $\frac{\text{Pos}}{\text{Neg+Pos}}$ | TN | FP | FN | TP | Prec | Rec | FP/P |
|---|---|---|---|---|---|---|---|---|---|---|
| 0.27565 | 50 | 51 | 0.505 | 604,454 | 1,156 | 105,702 | 2,254 | 0.661 | 0.0209 | 0.0107 |
| 0.27608 | 50 | 59 | 0.5413 | 604,504 | 1,106 | 105,761 | 2,195 | 0.665 | 0.0203 | 0.0102 |
| 0.27667 | 50 | 79 | 0.6124 | 604,554 | 1,056 | 105,840 | 2,116 | 0.6671 | 0.0196 | 0.0098 |
| 0.27732 | 56 | 50 | 0.4717 | 604,610 | 1,000 | 105,890 | 2,066 | 0.6738 | 0.0191 | 0.0093 |
| 0.27798 | 50 | 80 | 0.6154 | 604,660 | 950 | 105,970 | 1,986 | 0.6764 | 0.0184 | 0.0088 |
| 0.27869 | 50 | 67 | 0.5726 | 604,710 | 900 | 106,037 | 1,919 | 0.6807 | 0.0178 | 0.0083 |

$$
\begin{aligned}
\text{Prec}(p) &< \text{Prec}(p+\Delta p)\\
\frac{\text{TP}}{\text{FP}+\text{TP}} &< \frac{\text{TP}-\text{Neg}}{(\text{FP}-\text{Pos})+(\text{TP}-\text{Neg})}\\
&\vdots\\
\text{FP}\cdot\text{Pos} &< \text{TP}\cdot\text{Neg}\\
\frac{\text{FP}}{\text{TP}} &< \frac{\text{Neg}}{\text{Pos}}
\end{aligned}
\tag{6}
$$

Having no elements of the negative class in a $p$-interval will make precision decrease, so we will cut the $p$-values into bands with some minimum number of elements of each class. For each model, the `Keras/Analyze_Proba` directory has a spreadsheet like Table 3 for minimum number of class elements 5, 10, 25, 50, 100, 200, 400, 800, 1600, 3200, and 6400. An opportunity for future research (§5) is to develop a method to cut the $p$ output into the smallest possible bands such that Prec($p$) is an increasing function.

In Table 3, we have cut $p$ into bands such that each band has at least fifty elements of each of the negative and positive classes. The $p$ values in the table are the average of the minimum and maximum values of $p$ in the band. The full table is at `Analyze_Proba/RFC_Easy_Run_0_50_Slices.csv`.

At this level of granularity and in this range of $p$, the precision is an increasing function of $p$, and we can say that to get Precision $= 2/3$ we should set $\theta \approx 0.276$. Another run of the same model with different random seed gave $\theta \approx 0.279$.

For the the **third budgetary decision criterion**, that the minimum probability that each immediately dispatched ambulance is needed is at least 50%, with the metric $\text{Pos}/(\text{Neg}+\text{Pos}) \geq 0.50$, equivalent to $\text{Pos} \geq \text{Neg}$.

Table 4 shows that, if we zoom out to where each band has at least 6,400 elements in each class, cutting $p$ into only seventeen intervals, $\text{Pos}/(\text{Neg}+\text{Pos})$ generally increases, but even at this high level the metric decreases between $p = 0.1606$ and $p = 0.1689$. This third metric is highly volatile.

**Table 4**
Metrics on $p$ Output of Random Forest Classifier on the Hard Features with Minimum of 6400 Elements of Each Class in Each Band. Table accompanies §2.5.1

| $p$ | Neg | Pos | $\frac{\text{Pos}}{\text{Neg+Pos}}$ | TN | FP | FN | TP | Prec | Rec | FP/P |
|---|---|---|---|---|---|---|---|---|---|---|
| 0.1166 | 132,612 | 5,396 | 0.0391 | 132,612 | 472,998 | 5,396 | 102,560 | 0.1782 | 0.95 | 4.3814 |
| 0.1293 | 79,551 | 6,400 | 0.0745 | 212,163 | 393,447 | 11,796 | 96,160 | 0.1964 | 0.8907 | 3.6445 |
| 0.1336 | 57,673 | 6,400 | 0.0999 | 269,836 | 335,774 | 18,196 | 89,760 | 0.2109 | 0.8314 | 3.1103 |
| 0.137 | 42,946 | 6,400 | 0.1297 | 312,782 | 292,828 | 24,596 | 83,360 | 0.2216 | 0.7722 | 2.7125 |
| 0.1399 | 36,922 | 6,400 | 0.1477 | 349,704 | 255,906 | 30,996 | 76,960 | 0.2312 | 0.7129 | 2.3705 |
| 0.1432 | 35,947 | 6,400 | 0.1511 | 385,651 | 219,959 | 37,396 | 70,560 | 0.2429 | 0.6536 | 2.0375 |
| 0.1469 | 32,431 | 6,400 | 0.1648 | 418,082 | 187,528 | 43,796 | 64,160 | 0.2549 | 0.5943 | 1.7371 |
| 0.1509 | 30,786 | 6,400 | 0.1721 | 448,868 | 156,742 | 50,196 | 57,760 | 0.2693 | 0.535 | 1.4519 |
| 0.1553 | 25,477 | 6,401 | 0.2008 | 474,345 | 131,265 | 56,597 | 51,359 | 0.2812 | 0.4757 | 1.2159 |
| 0.1606 | 23,300 | 6,400 | 0.2155 | 497,645 | 107,965 | 62,997 | 44,959 | 0.294 | 0.4165 | 1.0001 |
| 0.1689 | 26,951 | 6,400 | 0.1919 | 524,596 | 81,014 | 69,397 | 38,559 | 0.3225 | 0.3572 | 0.7504 |
| 0.1806 | 21,160 | 6,400 | 0.2322 | 545,756 | 59,854 | 75,797 | 32,159 | 0.3495 | 0.2979 | 0.5544 |
| 0.1979 | 17,362 | 6,400 | 0.2693 | 563,118 | 42,492 | 82,197 | 25,759 | 0.3774 | 0.2386 | 0.3936 |
| 0.2199 | 16,065 | 6,400 | 0.2849 | 579,183 | 26,427 | 88,597 | 19,359 | 0.4228 | 0.1793 | 0.2448 |
| 0.2366 | 10,969 | 6,400 | 0.3685 | 590,152 | 15,458 | 94,997 | 12,959 | 0.456 | 0.12 | 0.1432 |
| 0.249 | 9,058 | 6,400 | 0.414 | 599,210 | 6,400 | 101,397 | 6,559 | 0.5061 | 0.0608 | 0.0593 |
| 0.2835 | 6,400 | 6,559 | 0.5061 | 605,610 | 0 | 107,956 | 0 | nan | 0 | 0 |

We tried two ways to estimate where Pos/(Neg + Pos) = 0.50, and both gave the same result.

Method 1: If we slice the $p$ results into bands with at least 100 elements of each class, partly shown in Table 5, there is no band with $p < 0.2692$ with Pos/(Neg + Pos) $\geq 0.5$ and no band with $p > 0.2733$ with Pos/(Neg + Pos) $\leq 0.5$, so we can say with some confidence that if we chose $\theta \approx 0.271$, each ambulance immediately dispatched will have at least a 50% chance of being needed.

**Table 5**

Metrics on $p$ Output of Random Forest Classifier on the Hard Features with Minimum of 100 Elements of Each Class in Each Band. Table accompanies §2.5.1

| $p$ | Neg | Pos | $\frac{\text{Pos}}{\text{Neg+Pos}}$ | TN | FP | FN | TP | Prec | Rec | FP/P |
|---|---|---|---|---|---|---|---|---|---|---|
| 0.2692 | 118 | 100 | 0.4587 | 603,564 | 2,046 | 104,738 | 3,218 | 0.6113 | 0.0298 | 0.019 |
| 0.2698 | 100 | 101 | 0.5025 | 603,664 | 1,946 | 104,839 | 3,117 | 0.6156 | 0.0289 | 0.018 |
| 0.2704 | 127 | 100 | 0.4405 | 603,791 | 1,819 | 104,939 | 3,017 | 0.6239 | 0.0279 | 0.0168 |
| 0.2711 | 108 | 100 | 0.4808 | 603,899 | 1,711 | 105,039 | 2,917 | 0.6303 | 0.027 | 0.0158 |
| 0.2718 | 111 | 100 | 0.4739 | 604,010 | 1,600 | 105,139 | 2,817 | 0.6378 | 0.0261 | 0.0148 |
| 0.2725 | 100 | 109 | 0.5215 | 604,110 | 1,500 | 105,248 | 2,708 | 0.6435 | 0.0251 | 0.0139 |
| 0.2733 | 100 | 149 | 0.5984 | 604,210 | 1,400 | 105,397 | 2,559 | 0.6464 | 0.0237 | 0.013 |

Method 2: We used a rolling sum of the Neg and Pos to intervals with enough Neg and Pos to smooth out the metric Pos/(Neg+Pos). With $p$ rounded to four decimal places we still have volatility at each value of $p$, and the metric gets close to the target value (0.50) many times over a large range. If we take the rolling average of the ten or twenty rows centered at that value of $p$, we see less volatility, but even in this small interval the Pos/(Neg+Pos) increases and decreases. With a window size of 20, however, the only values of $p$ where the metric is close to the target are in this range, so we can choose $\theta = 0.272$, and our two methods agree. The full chart, up to a window of size 2,000, is in `Analyze_Proba/RFC_Hard_Run_0_Round_4_Rolling_Intervals`.

**Table 6**
Smoothing Pos/(Neg+Pos) with Rolling Sums of Different Window Sizes. Table accompanies §2.5.1

| Window Size | 1 | | | 10 | | | 20 | | | 50 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $p$ | Neg | Pos | $\frac{\text{Pos}}{\text{Neg+Pos}}$ | Neg | Pos | $\frac{\text{Pos}}{\text{Neg+Pos}}$ | Neg | Pos | $\frac{\text{Pos}}{\text{Neg+Pos}}$ | Neg | Pos | $\frac{\text{Pos}}{\text{Neg+Pos}}$ |
| 0.2717 | 14 | 22 | 0.6111 | 144 | 166 | 0.4645 | 303 | 320 | 0.4864 | 754 | 771 | 0.4944 |
| 0.2718 | 12 | 18 | 0.6 | 153 | 159 | 0.4904 | 310 | 315 | 0.496 | 754 | 768 | 0.4954 |
| 0.2719 | 14 | 16 | 0.5333 | 143 | 164 | 0.4658 | 307 | 323 | 0.4873 | 758 | 757 | 0.5003 |
| 0.2720 | 12 | 13 | 0.52 | 152 | 156 | 0.4935 | 300 | 323 | 0.4815 | 756 | 745 | 0.5037 |
| 0.2721 | 26 | 13 | 0.3333 | 161 | 150 | 0.5177 | 296 | 312 | 0.4868 | 768 | 737 | 0.5103 |
| 0.2722 | 10 | 22 | 0.6875 | 159 | 149 | 0.5162 | 306 | 296 | 0.5083 | 755 | 726 | 0.5098 |
| 0.2723 | 17 | 7 | 0.2917 | 159 | 147 | 0.5196 | 309 | 291 | 0.515 | 756 | 717 | 0.5132 |
| Range of $p$ where $\left\|\frac{\text{Pos}}{\text{Neg+Pos}} - 0.50\right\| < 0.01$ | | | | | | | | | | | | |
| | | min($p$) | 0.2472 | | min($p$) | 0.2718 | | min($p$) | 0.2718 | | min($p$) | 0.2711 |
| | | max($p$) | 0.3076 | | max($p$) | 0.2726 | | max($p$) | 0.2722 | | max($p$) | 0.2722 |

### *2.5.2. 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, $\mathrm{FP}/\mathrm{P} = 0.05$, we need to find, for each model whether there exists a value of $p$ where FP/P is close to 0.05, then find the best $\theta$ interval in that neighborhood. Of those valid results, find the model that gives the most TP.

Table 7 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.

The Balanced Bagging model here is an interesting case that we will cover in the next section, §2.5.3.

**Table 7**
Comparing Models: Best results for each algorithm on the Hard features for budgetary criterion FP/P closest to 0.05. Table accompanies §2.5.2

| Algorithm | $\alpha$ | $\gamma$ | $p$ | TN | FP | FN | TP | FP/P |
|---|---|---|---|---|---|---|---|---|
| Bal RF | 0.5 | | 0.86 | 600,464 | 5,146 | 95,359 | 12,597 | 0.048 |
| Keras | 0.5 | 0.0 | 0.598 | 600,212 | 5,398 | 97,029 | 10,927 | 0.05 |
| Log Reg | 0.5 | | 0.549 | 600,212 | 5,398 | 100,764 | 7,192 | 0.05 |
| RUSBoost | | | 0.5 | 600,212 | 5,398 | 101,041 | 6,915 | 0.05 |
| AdaBoost | | | 0.501 | 600,212 | 5,398 | 101,131 | 6,825 | 0.05 |
| Bal Bag | | | 0.9 | 602,185 | 3,425 | 101,272 | 6,684 | 0.032 |
| RF | | | 0.258 | 600,212 | 5,398 | 102,135 | 5,821 | 0.05 |
| Easy Ens | | | 0.549 | 600,155 | 5,455 | 102,322 | 5,634 | 0.051 |

### *2.5.3. Detecting Model Failure*

We have found two ways a model can fail to give a decision threshold $\theta$ that will satisfy the budgetary criteria. The second one we will consider is the usual problem, that the model does not sufficiently separate the positive and negative classes to give enough correct recommendations. The other cause is more subtle, and we consider it first because we just saw it in Table 7, that for the Balanced Bagging algorithm, the value of FP/P closest to 0.05 (FP/P = 0.032) is not close to 0.05, and the cause of the failure is the numerics in the algorithm.

The RUSBoost algorithm on the hard features only gives values of $p$ in a tiny range, $p \in [0.499, 0.5011]$, but in that range of 00021 the 713,566 samples return 706,938 different values of $p$. That's about as close to "continuous" as a discrete function can get. Digging down into the results returned by the Balanced Bagging algorithm on the hard features, 99% of the values of $p$ are rounded to the nearest tenth, making the results extremely discrete. In Table 8, going from $p = 0.897$ to $p = 0.9$ we add 19,052 new samples that change the FP/P value from 0.11 to 0.03. The model results give no way to find a budgetary decision threshold $\theta$ that will give us a 5% increase in the number of ambulances dispatched to automated notifications from cell phones. This model may have too much volatility to be useful.

The Balanced Random Forest algorithm on the hard features has a similar quirk, that 93% of its $p$ values are rounded to the nearest hundredth, which explains the FP/P = 0.048 as the closest to 0.05 in Table 7. These two algorithms, Bal Bag and Bal RF, interestingly, had more detail in the Medium Features results and even more detail for the Easy features, which is the opposite of what most of the other algorithms did. The AdaBoost, Keras, Log Reg, and RUSBoost all had, from the 713,566 samples, about 700,000 unique values of $p$ for the hard features, 650,000 for the medium features, and 150,000 for the easy features. A breakdown of those numbers is given in `Value_Counts_y_proba.csv` in the `Keras/Analyze_Proba` folder, and the value counts of $p$ are given for each algorithm in files such as `BalBag_Hard_Value_Counts.csv`.

**Table 8**
Model Failure: Balanced Bagging Algorithm on the Hard Features with FP/P closest to 0.05. Table accompanies §2.5.3

| $p$ | Neg | Pos | TN | FP | FN | TP | FP/P |
|---|---|---|---|---|---|---|---|
| 0.896 | 1 | 0 | 593,725 | 11,885 | 90,679 | 17,277 | 0.110091 |
| 0.897 | 1 | 0 | 593,726 | 11,884 | 90,679 | 17,277 | 0.110082 |
| 0.9 | 8,459 | 10,593 | 602,185 | 3,425 | 101,272 | 6,684 | 0.031726 |
| 0.908 | 1 | 1 | 602,186 | 3,424 | 101,273 | 6,683 | 0.031717 |
| 0.913 | 1 | 0 | 602,187 | 3,423 | 101,273 | 6,683 | 0.031707 |

The second kind of model failure is the usual problem with machine learning models, that the algorithm is not successful in detecting enough of a pattern in the data to build a robust model that separates the positive and negative classes well. There are two likely reasons for the failure. One is that the particular algorithm with its hyperparameters is not suited to the kind of patterns in the data, and it is for this reason that we have tried several models with different class and focal weights. A second possible reason is that there just isn't enough of a pattern in the dataset, and it is for this reason that we have tested the Easy, Medium, and Hard feature sets.

As an example of this kind of model failure, consider the Random Forest Classifier on the Medium features, shown in Table 9. Here the $p$ values are cut into bands with at least one hundred elements of each of the Neg and Pos classes; the $p$ values in the first column are the average of the minimum and maximum $p$ value in the band.

The Precision values generally increase with $p$, and the table shows the end of the $p$ range; there are no values of Precision close to $2/3$, not because it doesn't theoretically exist, but the model is not robust enough to sufficiently separate the positive and negative classes. If the governmental leaders decided to change to Precision $= 1/2$, we could choose $\theta = 0.240$, but of the crash persons with an automated notification from a cell phone who needed an ambulance, we would only be immediately dispatching ambulances to Recall $= 1\%$ of them. Scaling that to a medium-sized city, the administrative overhead of the program might outweigh any benefit. Given a finite budget, a responsible government needs to choose the most cost-effective programs, and an immediate dispatch recommendation system might not be one of them.

We can see the problem also in a histogram of the model output, in Figure 10, where we compare the right tails of the output of the Random Forest model on the Medium features with the Example model from Figure 4. The model output has a long tail to the right, and zooming in on that tail, we see that in none of those intervals are there more elements of the positive class than the negative class.

Note that this range of $p$ in Table 9 is also where Pos/(Neg+Pos) crosses 0.50, meaning that there is a 50% marginal probability that the last ambulance sent will be needed, so we would have the same problem for that metric, that the model would recommend immediately dispatching ambulances to only about 1% of the automated notifications that needed an ambulance.

Fortunately we do have models with better results on the Medium features set.

**Table 9**
Metrics on Partial $p$ Output of Random Forest Classifier on the Medium Features with Minimum of 400 Elements of Each Class in Each Band. Table accompanies §2.5.3

| $p$ | Neg | Pos | $\frac{\text{Pos}}{\text{Neg+Pos}}$ | TN | FP | FN | TP | Prec | Rec | FP/P |
|---|---|---|---|---|---|---|---|---|---|---|
| 0.2386 | 415 | 401 | 0.491 | 603,883 | 1,727 | 106,283 | 1,673 | 0.492 | 0.016 | 0.016 |
| 0.2405 | 460 | 400 | 0.465 | 604,343 | 1,267 | 106,683 | 1,273 | 0.501 | 0.012 | 0.0117 |
| 0.2429 | 466 | 400 | 0.462 | 604,809 | 801 | 107,083 | 873 | 0.522 | 0.008 | 0.0074 |
| 0.2465 | 400 | 421 | 0.513 | 605,209 | 401 | 107,504 | 452 | 0.53 | 0.004 | 0.0037 |
| 0.2599 | 401 | 452 | 0.53 | 605,610 | 0 | 107,956 | 0 | nan | 0 | 0 |

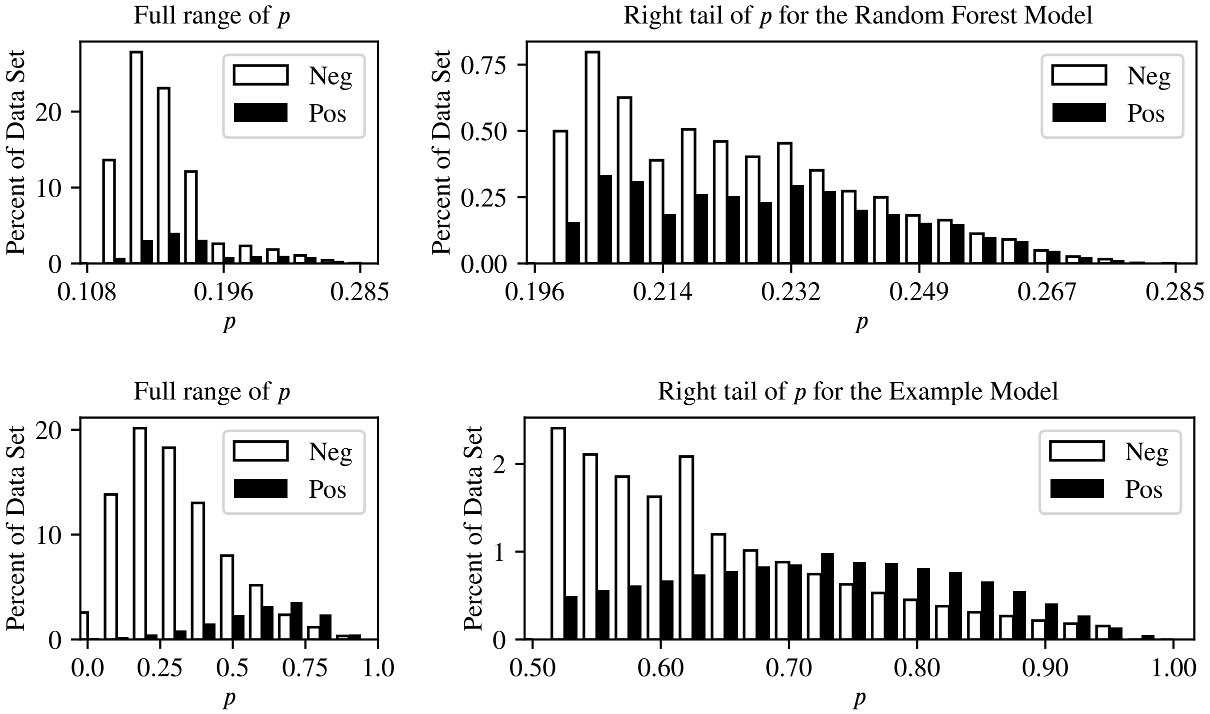


**Figure 10:** Random Forest Classifier on the Medium Features (top) and Example model (bottom). Figure accompanies §2.5.3

### *2.5.4. Numerical Precision*

We ran all of the models twice with different random seeds. As an example of the difference in model results, consider the first budgetary decision metric, the values of $p$ that make FP/P closest to 0.05, because that metric is the most stable. If there is a difference in those results between two runs of the same model for FP/P, not only can we only claim that much numerical precision in reporting our results for that metric, but we will probably need to limit ourselves to even less numerical precision in reporting results for the other budgetary decision metrics.

Table 10 shows the models with the largest changes between runs. The median $\Delta p$ was 0.0003, the median $\Delta$ TP was 57, and the median $\Delta$ FP was 1, giving median $\Delta$ FP/P of 0.0000093.

**Table 10**
Comparison of values of $p$, TP, FP, and FP/P between Runs of the Same Model with Different Random Seeds. Table accompanies §2.5.3

| Model | Features | Run | $p$ | Neg | Pos | FP | TP | FP/P | Notes |
|---|---|---|---|---|---|---|---|---|---|
| Keras $\alpha = 0.5$, $\gamma = 1.0$ | Medium | 0 | 0.50556 | 1 | 0 | 5,398 | 6,294 | 0.05 | $\Delta p = 0.012$ |
| Keras $\alpha = 0.5$, $\gamma = 1.0$ | Medium | 1 | 0.51764 | 1 | 0 | 5,398 | 6,105 | 0.05 | |
| Keras $\alpha = 0.5$, $\gamma = 1.0$ | Hard | 0 | 0.56429 | 1 | 0 | 5,398 | 10,946 | 0.05 | $\Delta$TP = 409 |
| Keras $\alpha = 0.5$, $\gamma = 1.0$ | Hard | 1 | 0.55914 | 1 | 0 | 5,398 | 10,537 | 0.05 | |
| Easy Ens | Easy | 0 | 0.52846 | 263 | 107 | 5,286 | 2,682 | 0.049 | $\Delta$FP = 180 |
| Easy Ens | Easy | 1 | 0.52866 | 27 | 15 | 5,466 | 2,741 | 0.0506 | $\Delta$FP/P = 0.0016 |

# 3. Results

## 3.1. Data and Image Files

Results data and images are in the `Keras/Analyze_Proba` and `Keras/Images` folders at `www.github.com/bburkman/Ambulance_Dispatch`. The results data are in `.csv` format, and the images in both `.png` and `.pgf`.

The results of each (algorithm, hyperparameters, features, random seed) combination are in, for example,

`LogReg_alpha_0_5_Easy_Run_0.csv` with $p$ in its full precision,
`LogReg_alpha_0_5_Easy_Run_0_Round_4.csv` with $p$ rounded and grouped,
`LogReg_alpha_0_5_Easy_Run_0_Rolling_Intervals.csv`,
`LogReg_alpha_0_5_Easy_Run_0_Round_4_Rolling_Intervals.csv`,
`LogReg_alpha_0_5_Easy_Run_0_Value_Counts_head_100.csv`
with the hundred most frequent values of $p$,
`LogReg_alpha_0_5_Easy_Run_0_{0,5,10,25,50,100,200,...,6400}_Slices.csv`
that each have $p$ cut into intervals with at least $n$ samples of each of the two classes.

For each (model, hyperparameters, features set, random seed) combination there are five images, for instance,

`BRFC_alpha_0_85_Easy_Run_0_Pred`,
`BRFC_alpha_0_85_Easy_Run_0_Pred_Wide`,
`BRFC_alpha_0_85_Easy_Run_0_Pred_Zoom`,
`BRFC_alpha_0_85_Easy_Run_0_Pred_Zoom_Wide`, and
`BRFC_alpha_0_85_Easy_Run_0_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 show $p$ from 0 to 1, and the `Zoom` images from the minimum to maximum values of $p$.

The summary tables, all `.csv` files, have one row for each (model, hyperparameters, features set, random seed) combination.

| | |
|---|---|
| `FP_P_0_05` | Value of $p$ with FP/P closest to 0.05 |
| `mProb_Rolling_0_500` | For each model and each window length in {1, 10, 20, 50, 100, 200, 500, 1000, 2000}, the first and last value of $p$ for which Pos/(Neg + Pos) is within 0.01 of 0.50. |
| `Prec_Rolling_0_667` | Same for Precision within 0.01 of 0.667 |
| `ROC_AUC` | ROC AUC |

## 3.2. Easy, Medium, and Hard Features

Figure 11 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 more to the left and the positive more to the right, better separating the two classes and giving a space (up to about $p = 0.8$) to choose a decision threshold $\theta$ 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, shown by the dashed line, 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.

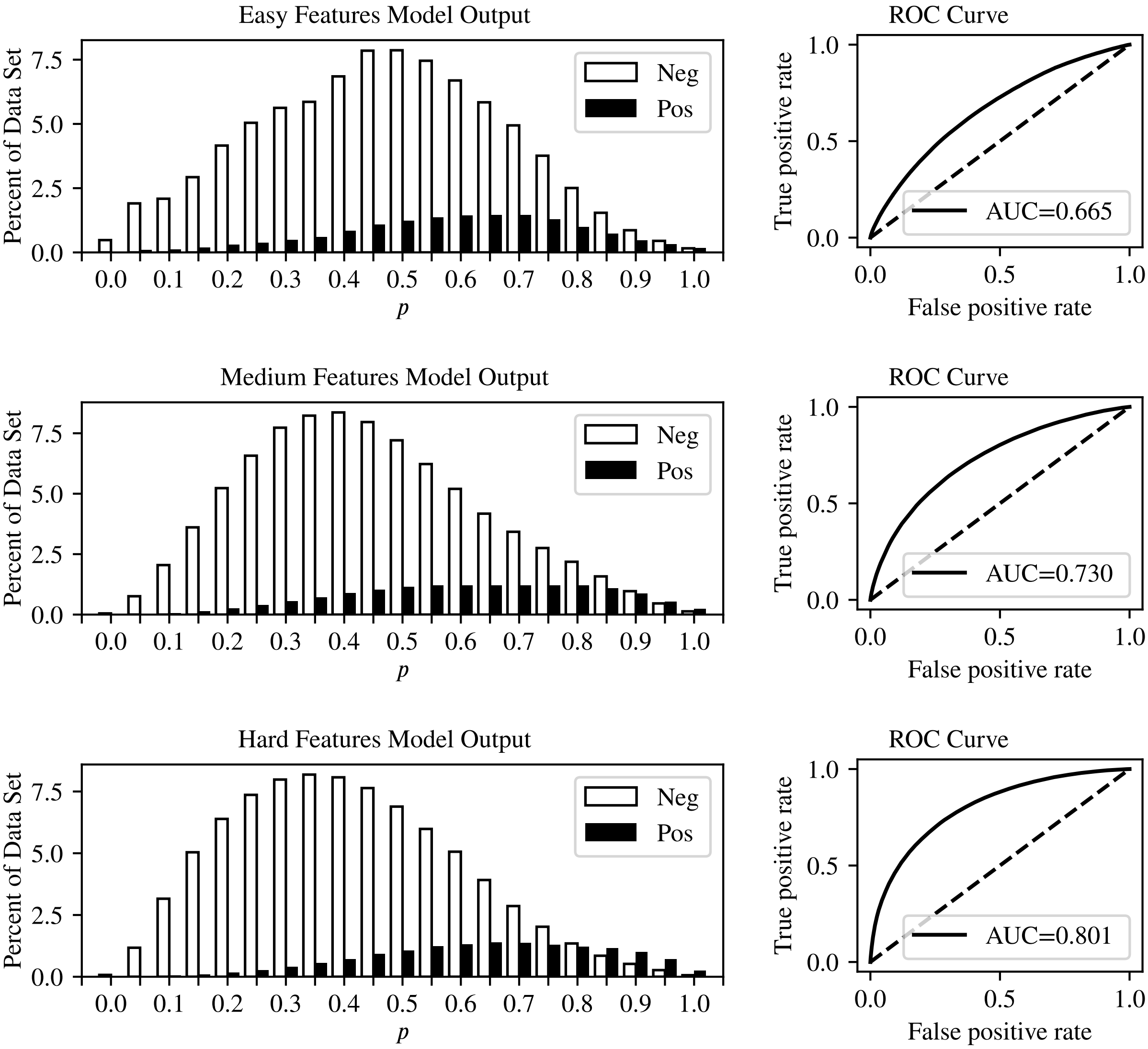


**Figure 11:** Balanced Random Forest Classifier with $\alpha = 0.5$ Model Results for Different Sets of Data Features. Figure accompanies §3.2

### 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%, with metric $\mathrm{FP}/\mathrm{P} \leq 0.05$. Table 11 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 $\theta$ to be the value of $p$ such that FP/P is closest to 0.05. In Table 11 we have included the best three models for each set of data features.

**Table 11**
Best models and transformations for FP/P = 0.05 for each algorithm. Table accompanies §3.3

| Model | Features | $p$ | TN | FP | FN | TP | FP/P | Recall |
|---|---|---|---|---|---|---|---|---|
| Bal RF, $\alpha = 0.5$ | Hard | 0.86 | 600,519 | 5,091 | 95,468 | 12,488 | 0.0472 | 0.1157 |
| Keras, $\alpha = 0.5$, $\gamma = 1.0$ | Hard | 0.5643 | 600,212 | 5,398 | 97,010 | 10,946 | 0.05 | 0.1014 |
| Log Reg, $\alpha = 0.5$ | Hard | 0.5477 | 600,212 | 5,398 | 100,715 | 7,241 | 0.05 | 0.0671 |
| Bal RF, $\alpha = 0.5$ | Medium | 0.89 | 600,288 | 5,322 | 101,267 | 6,689 | 0.0493 | 0.062 |
| Keras, $\alpha = 0.5$, $\gamma = 0.0$ | Medium | 0.5117 | 600,212 | 5,398 | 101,643 | 6,313 | 0.05 | 0.0585 |
| RF | Medium | 0.2581 | 600,212 | 5,398 | 102,135 | 5,821 | 0.05 | 0.0539 |
| Bal RF, $\alpha = 0.5$ | Easy | 0.8887 | 600,213 | 5,397 | 103,717 | 4,239 | 0.05 | 0.0393 |
| Bal Bag | Easy | 0.9 | 600,476 | 5,134 | 104,345 | 3,611 | 0.0476 | 0.0334 |
| Keras, $\alpha = 0.5$, $\gamma = 1.0$ | Easy | 0.4193 | 600,217 | 5,393 | 104,763 | 3,193 | 0.05 | 0.0296 |

We have not here included similar results, like the Balanced Random Forest models with different hyperparameters, because the data shows that 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. For full results see `Keras/Analyze_Proba/FP_P_0_05.csv`.

Our **second budgetary decision criterion** was that, of the ambulances immediately dispatched, at least 2/3 should be actually needed. Table 12 gives, for each feature set 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 $\theta$ to be the value of $p$ such that Precision $=$ TP/(FP + TP) is closest to 0.667 when Precision converges in rolling averages of FP and TP of increasing window size. For full results see `Keras/Analyze_Proba/Prec_Rolling_0_667.csv`.

The Hard features give robust models that immediately dispatch up to 19% of the needed ambulances while staying within the budgetary decision criterion, but the Medium models are bad and the Easy worthless. Most of the thirteen Easy models do not even get close to finding a $p$ where Precision is 2/3. Governments that wanted to consider models built on the Easy features could consider Precision of 1/2 as an attainable target.

**Table 12**
Best models and transformations for Precision = TP/(FP + TP) = 2/3 for each algorithm. Table accompanies §3.3

| Model | Features | $p$ | TN | FP | FN | TP | Prec | Recall |
|---|---|---|---|---|---|---|---|---|
| Bal RF, $\alpha = 0.5$ | Hard | 0.8199 | 594,922 | 10,688 | 87,467 | 20,489 | 0.6572 | 0.1898 |
| Keras, $\alpha = 0.5, \gamma = 1.0$ | Hard | 0.5631 | 599,135 | 6,475 | 95,560 | 12,396 | 0.6571 | 0.1148 |
| Bal Bag | Hard | 0.9567 | 602,204 | 3,406 | 101,142 | 6,814 | 0.6666 | 0.0631 |
| Bal RF, $\alpha = 0.5$ | Medium | 0.9671 | 604,992 | 618 | 106,770 | 1,186 | 0.6574 | 0.011 |
| Keras, $\alpha = 0.5, \gamma = 0.0$ | Medium | 0.749 | 605,478 | 132 | 107,705 | 251 | 0.6571 | 0.0023 |
| Log Reg, $\alpha = 0.5$ | Medium | 0.727 | 605,596 | 14 | 107,927 | 29 | 0.6574 | 0.0003 |
| AdaBoost | Easy | 0.4997 | 605,608 | 2 | 107,952 | 4 | 0.6667 | 0 |
| Keras, $\alpha = 0.5, \gamma = 1.0$ | Easy | 0.5445 | 605,608 | 2 | 107,952 | 4 | 0.6667 | 0 |
| Log Reg, $\alpha = 0.5$ | Easy | 0.4708 | 605,609 | 1 | 107,954 | 2 | 0.6667 | 0 |

Our **third budgetary decision criterion** was that each ambulance immediately dispatched should have at least a 50% chance of being needed. Table 13 gives, for each feature set 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 $\theta$ to be the value of $p$ such that the marginal probability, $m$Prob = Pos/(Neg + Pos), is closest to 0.50 when mProb converges in rolling sums of Neg and Pos of increasing window size. For full results see `Keras/Analyze_Proba/mProb_Rolling_0_500.csv`.

**Table 13**
Best models for $m$Prob = Pos/(Neg + Pos) $\approx$ 0.5 for each algorithm with length of rolling sum. Table accompanies §3.3

| Model | Features | Roll | $p$ | Neg | Pos | $m$Prob | TP | Recall |
|---|---|---|---|---|---|---|---|---|
| Bal RF, $\alpha = 0.5$ | Hard | 50 | 0.5214 | 3,217 | 3,275 | 0.5045 | 23,732 | 0.2198 |
| Keras, $\alpha = 0.5, \gamma = 1.0$ | Hard | 200 | 0.5415 | 2,446 | 2,535 | 0.5089 | 15,007 | 0.139 |
| Log Reg, $\alpha = 0.5$ | Hard | 500 | 0.5005 | 2,518 | 2,613 | 0.5093 | 6,916 | 0.0641 |
| RUSBoost | Hard | 100 | 0.8858 | 3,980 | 4,142 | 0.51 | 5,529 | 0.0512 |
| Bal RF, $\alpha = 0.5$ | Medium | 200 | 0.5006 | 2,266 | 2,339 | 0.5079 | 6,364 | 0.0589 |
| BalBag, $\alpha = 0.85$ | Medium | 20 | 0.5195 | 4,727 | 4,864 | 0.5071 | 4,668 | 0.0432 |
| Keras, $\alpha = 0.5, \gamma = 0.0$ | Medium | 500 | 0.5222 | 2,352 | 2,442 | 0.5094 | 4,409 | 0.0408 |
| Bal RF, $\alpha = 0.5$ | Easy | 500 | 0.5522 | 1,610 | 1,601 | 0.4986 | 760 | 0.007 |
| Keras, $\alpha = 0.85, \gamma = 0.0$ | Easy | 10 | 0.5174 | 12 | 12 | 0.5 | 33 | 0.0003 |

## 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 for a call from an eyewitness.

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. Another challenge is identifying with useful numerical precision the decision threshold $\theta$ that satisfies a given metric when the value of that metric is only stable after much smoothing. We found that finding $\theta$ for the first metric, a cap on increased ambulance runs, is straightforward, but Precision requires some smoothing, and marginal probability that an ambulance is needed is very unstable on small intervals.

The most significant challenge of implementing such a system is the cost and availability of 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. |
| §2.5.1 | 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.

## References

Chawla, N., Bowyer, K., Hall, L., Kegelmeyer, W., 2002. Smote: Synthetic minority over-sampling technique. JOURNAL OF ARTIFICIAL INTELLIGENCE RESEARCH 16, 321 – 357.

Herbert, G., 2019. Crash Report Sampling System: Imputation. Technical Report DOT HS 812 795. National Highway Traffic Safety Administration.

Lemaître, G., Nogueira, F., Aridas, C.K., 2017. Imbalanced-learn: A python toolbox to tackle the curse of imbalanced datasets in machine learning. Journal of Machine Learning Research 18, 1–5. URL: http://jmlr.org/papers/v18/16-365.html.

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.

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.

Raghunathan, T., Solenberger, P., Berglund, P., van Hoewyk, J., . Iveware: Imputation and variation estimation software. URL: https://www.src.isr.umich.edu/software/iveware/.