

## Highlights

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

First Author, Second Author, Third Author, Fourth Author

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

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

First Author<sup>a,b</sup>, Second Author<sup>a</sup>, Third Author<sup>a,c</sup> and Fourth Author<sup>c</sup>

<sup>a</sup>School, University,  
<sup>b</sup>Other School,  
<sup>c</sup>Other Department, University,

## ARTICLE INFO

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

## ABSTRACT

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

This paper explores one option for building a machine learning (ML) model for making a recommendation in the “Sometimes” option. Our goal is to build a model that returns, for each feature vector (crash report, sample), a value  $p \in [0, 1]$  that increases with the probability that the person needs an ambulance. Then we choose a threshold  $\theta$  such that we immediately send ambulances to those automated crash reports with  $p > \theta$ , and wait for eyewitness confirmation for those reports with  $p < \theta$ . In an actual implementation, the choice of  $\theta$  is political, not technical, so we consider and interpret several options.

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


We consider and interpret several 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, and we 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.

## Contents

0.1	Getting Probability from predict_proba . . . . .	3
1	Outline . . . . .	3

 FirstAuthor@gmail.com (F. Author)  
ORCID(s):

<b>2</b>	<b>Introduction</b>	<b>3</b>
2.1	Introduction . . . . .	3
2.1.1	Confusion Matrix . . . . .	4
2.2	Decision Threshold . . . . .	4
2.3	Simplifying Assumptions and Caveats . . . . .	6
<b>3</b>	<b>Total and Marginal Precision</b>	<b>6</b>
<b>4</b>	<b>Marginal</b>	<b>9</b>
4.1	Getting Probability from predict_proba . . . . .	9
<b>5</b>	<b>Literature Review</b>	<b>9</b>
<b>6</b>	<b>Dataset</b>	<b>9</b>
<b>7</b>	<b>Methods</b>	<b>9</b>
7.1	Goal . . . . .	10
7.2	Dataset . . . . .	10
7.3	Binning Categories . . . . .	10
7.4	Imputing Missing Data . . . . .	11
7.5	Order of Operations . . . . .	11
<b>8</b>	<b>Methods</b>	<b>11</b>
8.1	Metrics . . . . .	11
8.2	Incorporating the $\Delta FP / \Delta TP < \omega$ Ethical Threshold . . . . .	11
8.2.1	Class Weight . . . . .	12
8.2.2	Decision Threshold . . . . .	12
8.3	Preparing the Data . . . . .	13
8.3.1	Order of Operations . . . . .	13
8.3.2	Binning . . . . .	14
8.3.3	Imputing Missing Values . . . . .	14
8.4	Selecting Features . . . . .	14
8.5	Handling Imbalanced Data . . . . .	14
8.5.1	Resampling the Dataset . . . . .	15
8.5.2	Modifying the Loss Function . . . . .	16
8.5.3	Metrics for Imbalance . . . . .	16
8.5.4	ML Algorithms for Imbalanced Data . . . . .	17
8.6	Models . . . . .	17
8.7	Analysis of Results . . . . .	18
<b>9</b>	<b>Results</b>	<b>21</b>
<b>10</b>	<b>Conclusions</b>	<b>21</b>
<b>11</b>	<b>Discussion</b>	<b>21</b>
<b>12</b>	<b>Future Work</b>	<b>21</b>
<b>13</b>	<b>To Do, Notes to Self</b>	<b>21</b>
<b>14</b>	<b>Henry_07_22_23</b>	<b>21</b>

<b>15 To Henry, 22 July 2023</b>	<b>21</b>
15.1 Big Question . . . . .	21
15.2 Scenario . . . . .	22
15.3 Decision Threshold . . . . .	22
15.4 Understanding the Data . . . . .	23
15.4.1 Total Effects . . . . .	23
15.4.2 Marginal Effects of Moving the Decision Threshold . . . . .	24
15.5 Evaluating Models . . . . .	25
15.6 Example: Finding Decision Thresholds in One Model . . . . .	25
15.7 Answers to Political Questions for This Model . . . . .	26
15.8 Comparing Models . . . . .	28
15.9 Comparing Models over Three Sets of Features . . . . .	29
<b>16 Results</b>	<b>30</b>
16.1 Hard Features . . . . .	31
16.2 Balanced Random Forest Classifier, $\alpha$ balanced . . . . .	39
16.3 Medium Features . . . . .	71
16.4 Easy Features . . . . .	111

## 17 151

### 0.1. Getting Probability from predict\_proba

From the file `Marginal.tex`

Each of our models gives, for each sample  $x_i$ , a prediction  $\text{predict\_proba}(x_i) \in [0, 1]$  that the sample belongs to the positive class, *i.e.* that that crash person needs an ambulance. For some modeling algorithms, the prediction  $\text{predict\_proba}(x_i)$  is reasonably close to the posterior probability, but for other (otherwise useful) algorithms, we can only be confident that  $\text{predict\_proba}(x_i)$  increases with the probability  $P(y_i = 1|x_i)$ . ?

Because we are doing supervised learning (training and testing our model on data where we know the answer  $y_i \in \{0, 1\}$  to whether or not the crash person needed an ambulance), we can find the probabilities directly. If we choose ranges of  $\text{predict\_proba}(x_i)$  large enough to smooth out the randomness, we can find the probability in that range from the ratio of the number of samples for which  $y = 1$ .

Sophisticated algorithms exist for recalibrating the  $\text{predict\_proba}(x_i)$  to give the posterior probability. One such method, called Platt Scaling, learns a sigmoid transformation, and another process uses isotonic regression to learn a monotonically increasing mapping from  $\text{predict\_proba}(x_i)$  to the posterior probability. The scikit-learn method `calibration_curve` implements both methods.

From sklearn documentation <https://scikit-learn.org/stable/modules/calibration.html#calibration>

Factors in scoring: “calibration (reliability) and discriminative power (resolution) of a model, as well as the randomness of the data (uncertainty)”

## 1. Outline

## 2. Introduction

### 2.1. Introduction

When a cell phone detects the deceleration profile of an automobile crash, the cell service provider can first call the phone, and if there is no response, automatically notify local emergency services that they suspect a crash at a certain location. Before automated notifications, almost all crash notifications to emergency services came from an eyewitness who would report whether an ambulance was needed. With an automated crash notification, the emergency dispatcher will send a police officer to investigate, but should the dispatcher also immediately send an ambulance?

The political body setting the policy has three options.

**Always** Erring on the side of caution, dispatch an ambulance to every automated crash notification. Using our assumption that the CRSS data is representative of such crashes, about 85% will not need the ambulance, so this option has a False Positive Rate (FPR) of 85%.

**Never** Immediately dispatch police to investigate the crash, but wait for an eyewitness (perhaps the police) to say an ambulance is needed before sending one. About 15% of the crashes will need an ambulance, and this policy will delay sending the ambulance, so this option has a False Negative Rate of 15%.

**Sometimes** With the information available to emergency dispatchers at the time of the notification, use a machine learning model to calculate the probability  $p$  that the person whose phone sent an automated crash notification (“crash person”) needs an ambulance. Considering the marginal and total costs and benefits, choose a decision threshold  $\theta$  above which ( $p > \theta$ ) we automatically dispatch an ambulance. For each crash notification, if  $p > \theta$ , then dispatch an ambulance immediately. if  $p < \theta$ , wait for eyewitness confirmation before sending an ambulance. This option does not replace the existing system of eyewitnesses calling in a crash, so ambulances will get to crash scenes at least as soon as before; the goal is to identify crash persons likely to need an ambulance and get those ambulances there sooner.

This paper will explore the “Sometimes” option.

The machine learning model will not be perfect. It will return some false positives (dispatching an ambulance that is not needed and would not have been sent using only eyewitness notifications) and false negatives (not immediately dispatching an ambulance that is needed). False positives cost resources; false negatives cost lives.

### 2.1.1. Confusion Matrix

The confusion matrix gives the totals based on the model and choice of decision threshold. Let us interpret it in the language of our ambulance dispatch problem.

		Predicted	
		PP	PN
Actual	P	TP	FN
	N	FP	TN

P	Number of crash persons who need an ambulance; also the number to whom we will <i>immediately</i> or <i>eventually</i> send an ambulance
N	Number of crash persons who do not need an ambulance
PP	Number of crash persons to whom we immediately dispatch an ambulance
PN	Number of crash persons to whom we do not <i>immediately</i> dispatch an ambulance
TP	Number of crash persons to whom we immediately dispatch a needed ambulance
FN	Number of crash persons who need an ambulance, but to whom we do not <i>immediately</i> send one, but we will send one later when an eyewitness calls
FP	Number of crash persons to whom we dispatch an ambulance that is not needed
TN	Number of crash persons who do not need an ambulance and to whom we do not immediately (or ever) send one

$$\frac{TP}{FP + TP} = \frac{TP}{PP} \quad \text{Precision, the proportion of immediately dispatched ambulances that are needed}$$

$$\frac{TP}{FN + TP} = \frac{TP}{P} \quad \text{Accuracy, the proportion of crash persons needing an ambulance to whom we immediately dispatch one}$$

$$\frac{FP}{FN + TP} = \frac{FP}{P} \quad \text{Proportion of increase in number of ambulances sent because of immediate dispatch. The P number of ambulances would have been dispatched anyway, but now the FP number of ambulances are also being sent.}$$

## 2.2. Decision Threshold

Here’s something new from my last email.

How to determine the decision threshold is a political decision, not a technical one. We will consider three ways politicians might answer that question and how to implement each in our models and decision thresholds.

1. Our local fleet of ambulances now goes to  $n$  crashes per year. In the short term, without buying more ambulances and hiring more teams, we can increase the number of ambulance runs to crashes by some percentage, or in the longer term we are willing to increase the number of ambulances going to crashes by a larger, but still fixed, percentage.

We will use 5% as our example of how to implement this policy. The increase does not include the true positives (TP), because those ambulances would go anyway; the increase is the allowable number of false positives (FP). Set the decision threshold where the number of false positives is 5% of the positive class ( $P = FN + TP$ ).

$$\frac{FP}{P} = \frac{FP}{FN + TP} = 0.05$$

Lots of ratios of TN, FP, FN, and TP have names, but I haven't found a name for FP/P or where other people have used it.

2. We are willing to send ambulances based on automated crash reports, but only up to the point where a certain proportion of the ambulances we immediately dispatch (FP+TP) are actually needed (TP), which is equivalent to saying that we are willing to immediately send a certain number of unneeded ambulances for each one we automatically send that is needed.

This is what I was trying to get at with FP and TP, but I realized it's equivalent to Precision, which the readers will understand.

Choose the decision threshold where the precision is the specified level. We will use 1/3 for our example, being willing to send two FP for each TP.

3. By looking at the slope of the ROC curve we can (roughly) estimate the probability that a particular crash needs an ambulance. Some of them almost definitely need an ambulance, and we should dispatch those immediately, but we will choose a minimum probability to which we will immediately dispatch an ambulance.

I'm going to use 50% as an example of the minimum probability. The model assigns to each sample in the test set at value  $p \in [0, 1]$ . I had read that  $p$  was the probability that the sample was in the positive class, but I don't think that's exactly true. What is true is that  $p$  generally increases with probability.

In each sufficiently large\* range of  $p$  (like  $p \in [0.60, 0.61]$ ) there are some number of elements of the negative and positive class. For a given range of  $p$ , call the number of elements of the negative class "Neg" and the number of elements of the positive class "Pos." For the samples in that range of  $p$ , the probability that they are in the positive class is

$$\frac{\text{Pos}}{\text{Pos} + \text{Neg}}$$

This expression is proportional to the slope of the ROC curve at that value of  $p$ .

I want to call this "marginal precision," but I haven't seen that term used that way in the ML literature. I think "marginal precision" means something else in statistics. See that

$$\text{Pos} = \frac{\Delta TP}{\Delta p}, \quad \text{Neg} = \frac{\Delta FP}{\Delta p}, \quad \text{and} \quad \text{Pos} + \text{Neg} = \frac{\Delta(TP + FP)}{\Delta p}, \quad \text{so} \quad \frac{\text{Pos}}{\text{Pos} + \text{Neg}} = \frac{\Delta TP}{\Delta(TP + FP)}$$

\*We have two challenges with choosing  $\Delta p$ , the size of our range of  $p$ , which we would like to be really small. One is that some of our ML algorithms return (almost all) values of  $p$  rounded to two decimal places, so we can't get more precision than that. One of my algorithms (Balanced Bagging) gives  $p$  for each sample to only one decimal place; thus, "sufficiently large" depends on the algorithm.

The other problem is that if you zoom in too close, the number of samples in each  $\Delta p$  isn't large enough to compensate for the randomness, and you see that your "curve" is actually jagged. Because I wanted more samples in my test set, I went from using a 70/30 train/test split to using 5-fold validation, where all of the samples are in a test set.

### 2.3. Simplifying Assumptions and Caveats

- We may use “police” to mean “emergency services” or “emergency dispatcher.” We use “ambulance” to signify both the vehicle and the associated team of emergency medical technicians.
- The Google Pixel phone has had such a car crash detection feature since 2019. Apple said in 2020 that it would introduce such an app, but did not release it until the iPhone 14 (2022). It is also available on some Apple Watches.
- We use the CRSS dataset as if it were representative of the kinds of crash persons whose phones would send an automated notification to emergency services. Ideally, we would have a large ( $> 100,000$ ) set of detailed records of crashes that spawned an automated crash report, and Google and Apple may have such records, but to our knowledge no such data set is publicly available. A paper using private data on the crashes that resulted in automated notifications would be very valuable to the discussion, but readers would not be able to replicate the results and adapt the methods.
- Not having seen actual data on automated notifications, we do not know what proportion of crashes result in an automated notification, nor do we know what proportion of automated notifications need an ambulance. We are making the heroic assumption that the crashes in the CRSS data are a good proxy for crashes with automated notifications to emergency services.

### 3. Total and Marginal Precision

Given a model and a choice of decision threshold  $\theta$ , the total number of needed ambulances we send (TP) divided by the total number we send (FP + TP) is called the *precision*. Note that TP is all of the elements of the positive class with  $p > \theta$ , FP is all of the elements of the negative class with  $p > \theta$ , and FP+TP is all of the elements of either class with  $p > \theta$ .

The *marginal precision* at  $\theta$  is the ratio of the number of positive samples to the total number of samples in the neighborhood of  $p$  around  $\theta$ . The marginal precision the minimum probability that an ambulance sent is needed. In the language of economics, it is the probability that last ambulance sent is needed.

For example, if the decision makers are willing to send two unneeded ambulances (FP =  $2k$  for some  $k$ ) for every one that is needed (TP =  $1k$ ), we look for the value of  $p$  where  $\text{Prec} = \frac{1}{2+1} = 1/3$ . If we want each ambulance sent to have at least a  $1/3$  probability of being needed, then we look for the neighborhood of  $p$  where  $m\text{Prec} = 1/3$ .

The marginal precision is equivalent to the slope of the ROC curve, as there is an invertible mapping between them.

$$\begin{aligned}
 m\text{ROC} &= \frac{\Delta\text{TPR}}{\Delta\text{FPR}} = \frac{\Delta(\text{TP}/P)}{\Delta(\text{FP}/N)} \\
 &= \frac{(\Delta\text{TP})/P}{(\Delta\text{FP})/N} \quad (\text{because in a given model on a given data set, } P \text{ and } N \text{ are constant}) \\
 &= \frac{N}{P} \cdot \frac{\Delta\text{TP}}{\Delta\text{FP}} = \frac{N}{P} \cdot \frac{\Delta\text{TP}/\Delta p}{\Delta\text{FP}/\Delta p} = \frac{N}{P} \cdot \frac{\text{Pos}}{\text{Neg}} \\
 &= \frac{N}{P} \cdot \frac{1}{\frac{\text{Neg}}{\text{Pos}}} = \frac{N}{P} \cdot \frac{1}{\frac{\text{Neg}}{\text{Pos}} + 1 - 1} = \frac{N}{P} \cdot \frac{1}{\frac{\text{Neg} + \text{Pos}}{\text{Pos}} - 1} = \frac{N}{P} \cdot \frac{1}{\frac{1}{m\text{Prec}} - 1} = \frac{N}{P} \cdot \frac{m\text{Prec}}{1 - m\text{Prec}} \\
 m\text{Prec} &= \frac{P \cdot m\text{ROC}}{N + P \cdot m\text{ROC}}
 \end{aligned}$$

A challenge with calculating the marginal precision is choosing the margin  $\epsilon$  for the neighborhood about  $p$ . If we make  $\epsilon$  just large enough, the marginal precision will be a decreasing function of  $p$  and we will glean one value of  $\theta$  where  $m\text{Prec}$  is closest to the goal. Because our data set is discrete, however, too small values of  $\epsilon$  will yield some neighborhoods with few or no values of the positive or negative class. Because two of our model algorithms give most values of  $p$  rounded to two decimal places, we have chosen to use one hundred non-overlapping intervals of  $p$  ( $\epsilon = 0.005$ ) for our analysis.

The table below gives the values for each of a hundred  $p$  neighborhoods for one of our models. Looking at  $p = 0.45$  and  $0.46$ , for instance, for  $p \in [0, 0.45]$  the model has correctly classified 117,225 of the 180,245 elements of the negative class and 26,573 of the 33,825 elements of the positive class. Moving from  $p = 0.45$  to  $p = 0.46$ , the model correctly classifies 3,079 more elements of the negative class and 436 fewer elements of the positive class.

Claim: The precision is an increasing function is equivalent to

$$\frac{\text{Pos}}{\text{Neg}} < \frac{\text{TP}}{\text{FP}}$$

which is not necessarily true if we zoom in to a sufficiently small interval of  $p$ , because of the stochastic and discrete nature of our data set. Over sufficiently large intervals of  $p$ , however, it is generally true that precision is an increasing function of the decision boundary  $\theta$ , being equivalent to the ROC curve curving down.

If the politicians have decided that they will trade off two immediately dispatched ambulances for each needed ambulance, then we choose the decision threshold  $\theta$  at the value of  $p$  where  $\text{Prec} = 0.33$ , which happens around  $p = 0.49$ . Note that in this case we would be sending some ambulances to some crashes where there is only a 15% chance that the ambulance is needed. Similarly for other political decisions about total tradeoffs; we will investigate  $\text{Prec} = 1/2$  and  $\text{Prec} = 2/3$ .

If the politicians decide that they want to automatically dispatch ambulances only to notifications where the likelihood that the victim requires an ambulance is greater than  $1/3$ , then choose the decision threshold  $\theta$  at the value of  $p$  where  $m\text{Prec} = 0.33$ , which happens around  $p = 0.68$ . The marginal precision is much more volatile than the total precision, but we can narrow it down to somewhere in that region. At this value of  $\theta$  over half,  $13,617/(12,766 + 13,617) \approx 0.52$ , of the ambulances that we automatically dispatch turn out to be needed. Similarly for other politically-chosen minimum percentages; we will also investigate  $1/2$  and  $2/3$ .



Balanced Random Forest Classifier, Hard features, No Tomek undersampling, No class weights, Test set, Version 1

p	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	$\hat{p}$
0.00	107	0	0.00	107	180,138	0	33,825	0.16	1.00	1.00
0.01	238	3	0.01	345	179,900	3	33,822	0.16	1.00	1.00
0.02	331	2	0.01	676	179,569	5	33,820	0.16	1.00	1.00
0.03	441	3	0.01	1,117	179,128	8	33,817	0.16	1.00	0.99
0.04	526	6	0.01	1,643	178,602	14	33,811	0.16	1.00	0.99
0.05	751	6	0.01	2,394	177,851	20	33,805	0.16	1.00	0.99
0.06	854	8	0.01	3,248	176,997	28	33,797	0.16	1.00	0.98
0.07	1,060	9	0.01	4,308	175,937	37	33,788	0.16	1.00	0.98
0.08	1,235	13	0.01	5,543	174,702	50	33,775	0.16	1.00	0.97
0.09	1,375	16	0.01	6,918	173,327	66	33,759	0.16	1.00	0.97
0.10	1,653	16	0.01	8,571	171,674	82	33,743	0.16	1.00	0.96
⋮										⋮
0.45	3,206	424	0.12	117,225	63,020	7,252	26,573	0.30	0.79	0.42
0.46	3,079	436	0.12	120,304	59,941	7,688	26,137	0.30	0.77	0.40
0.47	3,021	547	0.15	123,325	56,920	8,235	25,590	0.31	0.76	0.39
0.48	2,990	453	0.13	126,315	53,930	8,688	25,137	0.32	0.74	0.37
0.49	3,020	533	0.15	129,335	50,910	9,221	24,604	0.33	0.73	0.35
0.50	2,874	501	0.15	132,209	48,036	9,722	24,103	0.33	0.71	0.34
0.51	2,804	533	0.16	135,013	45,232	10,255	23,570	0.34	0.70	0.32
0.52	2,675	542	0.17	137,688	42,557	10,797	23,028	0.35	0.68	0.31
0.53	2,543	526	0.17	140,231	40,014	11,323	22,502	0.36	0.67	0.29
0.54	2,438	545	0.18	142,669	37,576	11,868	21,957	0.37	0.65	0.28
0.55	2,350	579	0.20	145,019	35,226	12,447	21,378	0.38	0.63	0.26
⋮										⋮
0.60	1,877	587	0.24	155,512	24,733	15,419	18,406	0.43	0.54	0.20
0.61	1,756	597	0.25	157,268	22,977	16,016	17,809	0.44	0.53	0.19
0.62	1,674	632	0.27	158,942	21,303	16,648	17,177	0.45	0.51	0.18
0.63	1,611	604	0.27	160,553	19,692	17,252	16,573	0.46	0.49	0.17
0.64	1,582	586	0.27	162,135	18,110	17,838	15,987	0.47	0.47	0.16
0.65	1,439	618	0.30	163,574	16,671	18,456	15,369	0.48	0.45	0.15
0.66	1,376	561	0.29	164,950	15,295	19,017	14,808	0.49	0.44	0.14
0.67	1,288	637	0.33	166,238	14,007	19,654	14,171	0.50	0.42	0.13
0.68	1,241	554	0.31	167,479	12,766	20,208	13,617	0.52	0.40	0.12
0.69	1,082	631	0.37	168,561	11,684	20,839	12,986	0.53	0.38	0.12
0.70	1,053	570	0.35	169,614	10,631	21,409	12,416	0.54	0.37	0.11
0.71	922	587	0.39	170,536	9,709	21,996	11,829	0.55	0.35	0.10
0.72	897	559	0.38	171,433	8,812	22,555	11,270	0.56	0.33	0.09
0.73	783	587	0.43	172,216	8,029	23,142	10,683	0.57	0.32	0.09
0.74	831	558	0.40	173,047	7,198	23,700	10,125	0.58	0.30	0.08
0.75	711	602	0.46	173,758	6,487	24,302	9,523	0.59	0.28	0.07
⋮										⋮
0.95	74	251	0.77	180,091	154	33,222	603	0.80	0.02	0.00
0.96	61	211	0.78	180,152	93	33,433	392	0.81	0.01	0.00
0.97	55	168	0.75	180,207	38	33,601	224	0.85	0.01	0.00
0.98	22	125	0.85	180,229	16	33,726	99	0.86	0.00	0.00
0.99	12	66	0.85	180,241	4	33,792	33	0.89	0.00	0.00
1.00	4	33	0.89	180,245	0	33,825	0	nan	0.00	0.00

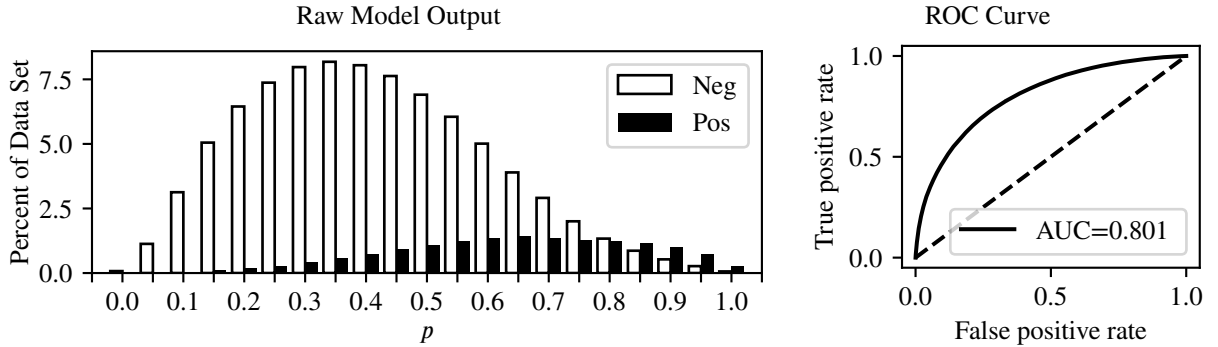
Visually on the histogram below, when we say that the precision of  $1/3$  happens at  $p \approx 0.50$ , we mean that on the interval  $p \in [0.50, 1.0]$ , the area under the Neg curve is twice the area under the Pos curve. When we say that the marginal precision of  $1/3$  happens at  $p \approx 0.7$ , we mean that the Neg bar at  $p = 0.7$  is twice as tall as the Pos bar.

On the ROC curve below,  $m\text{Prec} = 1/3$  happens at  $p \approx 0.7$ , on the curve at  $(\text{FPR}, \text{TPR}) = (0.06, 0.37)$  because

$$\text{FPR} = \frac{\text{FP}}{\text{N}} = \frac{10,631}{180,091} = 0.06 \quad \text{and} \quad \text{TPR} = \frac{\text{TP}}{\text{P}} = \frac{12,416}{33,825} = 0.37$$

and at that point

$$m\text{ROC} = \frac{\text{N}}{\text{P}} \cdot \frac{m\text{Prec}}{1 - m\text{Prec}} = \frac{180,254}{33,825} \cdot \frac{1/3}{1 - 1/3} \approx 3$$



## 4. Marginal

### 4.1. Getting Probability from predict\_proba

From the file `Marginal.tex`

Each of our models gives, for each sample  $x_i$ , a prediction  $\text{predict\_proba}(x_i) \in [0, 1]$  that the sample belongs to the positive class, *i.e.* that that crash person needs an ambulance. For some modeling algorithms, the prediction  $\text{predict\_proba}(x_i)$  is reasonably close to the posterior probability, but for other (otherwise useful) algorithms, we can only be confident that  $\text{predict\_proba}(x_i)$  increases with the probability  $P(y_i = 1|x_i)$ . ?

Because we are doing supervised learning (training and testing our model on data where we know the answer  $y_i \in \{0, 1\}$  to whether or not the crash person needed an ambulance), we can find the probabilities directly. If we choose ranges of  $\text{predict\_proba}(x_i)$  large enough to smooth out the randomness, we can find the probability in that range from the ratio of the number of samples for which  $y = 1$ .

Sophisticated algorithms exist for recalibrating the  $\text{predict\_proba}(x_i)$  to give the posterior probability. One such method, called Platt Scaling, learns a sigmoid transformation, and another process uses isotonic regression to learn a monotonically increasing mapping from  $\text{predict\_proba}(x_i)$  to the posterior probability. The scikit-learn method `calibration_curve` implements both methods.

From sklearn documentation <https://scikit-learn.org/stable/modules/calibration.html#calibration>

Factors in scoring: “calibration (reliability) and discriminative power (resolution) of a model, as well as the randomness of the data (uncertainty)”

## 5. Literature Review

### 6. Dataset

### 7. Methods

### 7.1. Goal

The goal of this paper is to show one method for determining, for different levels of available data and criteria reflecting different political choices, how well a machine learning model can predict whether an emergency call center should automatically dispatch an ambulance based on an automated crash notification.

Usually a crash notification comes to an emergency dispatcher from an eyewitness who can say whether there are injuries requiring medical attention. With an automated crash notification, however, that information is not available. We want to know whether, or to what degree, we can infer from information that is available whether it is likely that the phone's user needs an ambulance, and thus whether we should automatically dispatch an ambulance to the scene.

We will use an existing dataset to build models that give us the probability. For each of several different political realities and goals, we will choose the most useful model and find a threshold above which the emergency call center should automatically dispatch an ambulance. We will consider three different levels of available information, with "Easy" using information already available, "Medium" adding information that requires a higher level of planning and preparation, and "Hard" requiring cooperation between public and private data sources with possible conflicts of privacy and confidentiality.

From the results, a local government would have information on which to base a decision about whether to implement an automated dispatch system and what level of data to provide. The ultimate decision is political, weighing lives against money.

### 7.2. Dataset

Ideally, we would use a dataset of crashes with 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.

We will use the Crash Report Sampling System (CRSS) 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, between 2 and 3 percent. Since most 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 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.

We merged the `accident.csv`, `vehicle.csv`, and `person.csv` files in the six years. We dropped many features that were irrelevant, most because they were unique to each vehicle like a VIN (Vehicle Identification Number), with no predictive power, just random noise. We also dropped the 33,776 persons in crashes involving a pedestrian, because the deceleration profile of hitting a pedestrian or bicycle would not be different enough from hard braking to trigger an automated crash notification.

After removing repeated and irrelevant features and pedestrian crashes, we have 118 features describing 713,566 crash persons. Later we removed more that have more than 20% of the values missing or only have data for some years, and features with imputed missing values to get 78 features.

For full details, see the `Ambulance_Dispatch_01_Get_Data.ipynb` file.

### 7.3. Binning Categories

All of the CRSS data is discrete, but some features are ordered, like `HOURL` and `AGE`, and others are unordered, like `MAKE_MOD`. Reducing the dimensionality of the machine learning modeling by binning the categories into less than ten per feature is ideal.

Some features like `HOURL` we binned by hand. We looked at the proportion of crash persons hospitalized at each hour and found clear places to break it into seven contiguous but not equal blocks. When we looked at `AGE`, we considered breaking it into decades, but found that ages 15-18 have a far lower hospitalization rate than those a little younger or older, and there was a shift at about age 53 and again around age 74, so we binned it accordingly.

Some features like `MAKE_MODm` which has 1,210 unique values, we binned by imposing an order, ordering by the proportion of crash persons hospitalized, then cutting the ordered list into five new categories plus "Unknown."

For full details, see `Ambulance_Dispatch_02_Correlation.ipynb` and `Ambulance_Dispatch_03_Bin_Data.ipynb`.

## 7.4. Imputing Missing Data

For reasons of historical consistency going back to 1982 with the predecessors of CRSS, CRSS imputes missing values for some features but not others, using IVEware, Imputation and Variation Estimation Software from the Institute for Social Research at the University of Michigan. Fortunately, when CRSS gives a feature with imputed values, it also retains the feature with values signifying “Unknown.” CRSS has a very helpful report on its imputation methods. We have not seen in the literature where someone has used IVEware to impute the other features and compared it to other methods.

At this point we have 78 unimputed features, and only 250,389 out of 713,566 samples (35%) did not have missing values in those 78 features. We compared three methods for imputing missing values.

- IVEware
- Imputation to Mode
- Round-Robin Random Forest using Imputation to Mode as the starting point

We found that the Random Forest method was best.

For full details and analysis, see `Ambulance_Dispatch_04_Impute_Missing_Data.ipynb`.

## 7.5. Order of Operations

We also considered whether the order of operations made a difference, whether we should bin first, then impute, or impute using the raw data, then bin. We tried both methods over several runs and found that the difference between methods was about the same as the difference between runs of the same method with different random seeds. Since IVEware can only handle up to about forty categories in each categorical field, we had had to bin some fields first either way, so we chose to bin first, then impute.

For full details and analysis, see `Ambulance_Dispatch_05_IVEware_Order_of_Operations.ipynb`.

# 8. Methods

## 8.1. Metrics

**Precision** tells us, of the ambulances we sent, how many were needed. **Recall** tells us, of the ambulances that were needed, how many we sent. Recall only looks at elements of the minority class (positive class, “need ambulance”), so is independent of the class imbalance. Precision is affected by class imbalance, but is still relevant to our decisions in its imbalanced form. Because the number of elements of the positive class in the test set is constant across all of our models, recall is proportional to TP.

The **F1 score** is the harmonic mean of precision and recall. Why the harmonic mean instead of the arithmetic or geometric? For two positive numbers  $a$  and  $b$  with  $0 < a < b$ ,

$$a < Harm(a, b) < Geo(a, b) < Arith(a, b) < b$$

so the F1 score emphasizes what the model does poorly. We will use F1 as our primary indicator, while looking at precision and recall.

The area under the curve (AUC) of the receiver operating characteristic (ROC) is a measure of how well a model separates the samples of the positive and negative classes. We will use it to show that the additional features in the “hard/expensive” and “medium” datasets are important for discriminating between the two classes.

The  $\Delta FP/\Delta TP$  curve is related to the ROC;  $\Delta FP/\Delta TP$  is the reciprocal of the product of the slope of the ROC curve and a factor that corrects for class imbalance.

$$\frac{\Delta FP}{\Delta TP} = \frac{N}{P} \cdot \frac{\frac{\Delta FP}{N}}{\frac{\Delta TP}{P}} = \frac{N}{P} \cdot \frac{\Delta FPR}{\Delta TPR} = \frac{1}{\frac{P}{N} \cdot \frac{\Delta TPR}{\Delta FPR}} = \frac{1}{\frac{P}{N} \cdot mROC}$$

We will use this curve to find the value of the discrimination threshold where  $\Delta FP/\Delta TP = 2.0$

## 8.2. Incorporating the $\Delta FP/\Delta TP < \omega$ Ethical Threshold

We incorporated this ethical threshold in two ways, as a class weight and as the decision threshold.

### 8.2.1. Class Weight

To understand why class weights can encode this threshold, we will use the  $\alpha$ -weighted binary crossentropy model as an example.

To move the model towards  $\Delta FP / \Delta TP < \omega \rightarrow \Delta FP - \omega \Delta TP < 0$  is equivalent to minimizing  $FP - \omega TP$ . The  $\alpha$ -weighted binary crossentropy loss function is

$$Loss = - \left( \alpha \sum_{y=1} \log(h_{\theta}(x_i)) + (1 - \alpha) \sum_{y=0} \log(1 - h_{\theta}(x_i)) \right)$$

In this function,  $y_i \in \{0, 1\}$  is the ground truth for sample  $i$ , 0 if in the majority class ("no ambulance") and 1 if in the minority class ("yes ambulance"). The term  $h_{\theta}(x_i) \in [0, 1]$  is the probability that  $x_i$  is in the minority class, as calculated by this  $\theta$  iteration of the model.

The TN, FP, FN, and TP are discrete, and the  $h_{\theta}(x_i)$  is continuous. To see how they relate, let us discretize the loss function, with

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

which makes  $\sum_{y=1} \log(h_{\theta}(x_i))$  into  $TP$  and  $\sum_{y=0} \log(1 - h_{\theta}(x_i))$  into  $TN$ , making the discrete version of the loss function

$$Loss = -(\alpha TP + (1 - \alpha)TN)$$

In the following manipulations, note that adding a constant, or multiplying by a positive constant, does not change the effect of the loss function, which the model algorithm uses to compare one iteration to the next.

$$Loss = -(\alpha TP + (1 - \alpha)TN)$$

$$Loss = - \left( \frac{\omega}{\omega + 1} TP + \frac{1}{\omega + 1} TN \right) \quad \text{Let } \alpha = \frac{\omega}{\omega + 1}, \text{ making } 1 - \alpha = \frac{1}{\omega + 1}$$

$$Loss = -(\omega \cdot TP + TN) \quad \text{Multiply by } \omega + 1$$

$$Loss = -(\omega \cdot TP + TN) + TN + FP \quad \text{Add constant } TN + FP, \text{ the number of majority samples}$$

$$Loss = FP - \omega \cdot TP$$

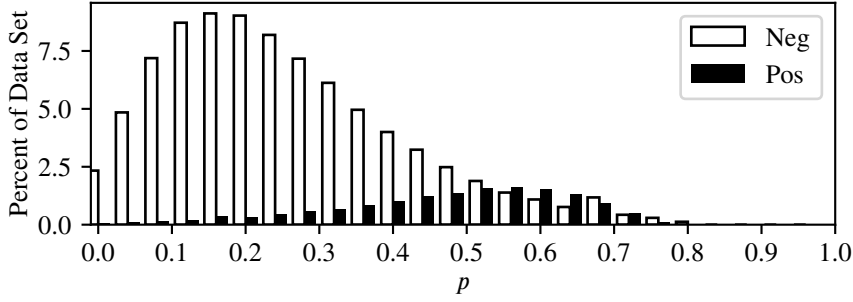
Thus, we can incorporate the ethical threshold  $p$  into our loss function as the class weight. For this study we have arbitrarily chosen  $\omega = 2$ , so we will use class weight  $\alpha = \omega / (\omega + 1) = 2/3$ .

### 8.2.2. Decision Threshold

Once a supervised learning algorithm learns a model using the training set, it evaluates the model on the test set, returning for each sample in the test set a probability  $p \in [0, 1]$  that the sample belongs to the positive class ("need ambulance"). By default we use a decision threshold  $p = 0.5$  to discriminate between predicted negative (PN) and predicted positive (PP), but for good cause we can choose a different threshold. We will choose to make the decision threshold the value of  $p$  that makes  $\Delta FP / \Delta TP = 2$ . Because many tools are built around having the decision threshold at  $p = 0.5$ , rather than change the decision threshold we will linearly transform the probabilities  $p \in [0, 1]$  to shift the desired threshold of  $p$  where  $\Delta FP / \Delta TP = 2$  to  $p = 0.5$ .

Consider these results from one of our models. The histogram shows, for the negative ("no ambulance") and positive ("ambulance") classes, the percentage of the dataset in each range of  $p$ . In an ideal model, the negative class would be clustered on the left and the positive on the right. The ROC curve and the area under the curve (AUC) indicates how cleanly the model separates the two classes, with  $AUC = 1$  being perfect and  $AUC = 0.5$  being basically random classification.

### Ambulance Dispatch



Raw Model Output

ROC Curve

		Prediction	
		N	P
Actual	N	118,776	31,995
	P	10,572	16,049

0.334 Precision  
0.603 Recall  
0.430 F1

Mapping  $\Delta FP/\Delta TP$  as a function of  $p$  for this model, we see that it equals  $\omega = 2$  when  $p = 0.720$ . Using a linear transformation, we can map 0.720 to 0.5, keeping 0 at 0, to get transformed model output with the decision threshold where  $\Delta FP/\Delta TP = 2$ . The ROC curve and its AUC are invariant under such a transformation.

$\Delta FP/\Delta TP$  as a function of  $p$

Transformed Model Output

		Prediction	
		N	P
Actual	N	142,035	8,736
	P	18,549	8,072

0.480 Precision  
0.303 Recall  
0.372 F1  
0.774 AUC

It is reasonable to ask, “How is the transformed model ethically better? We are only sending 8,072 needed ambulances instead of 16,049. In the original model,  $FP/TP = 31,995/16,049 = 1.994 < 2.0 = \omega$ . How is it better to send half as many needed ambulances?” Because our ethical tradeoff was not for total number of FP and TP, but for marginal FP and TP. Going from the original to the transformed model, we have  $\Delta FP/\Delta TP = (31,995 - 8,736)/(16,049 - 8,072) = 23,259/7,977 = 2.91$ , which is higher than our choice of ethical tradeoff  $\omega = 2.0$ . For this model, it is at  $p = 0.720$  that we reach our tradeoff point.

We will use the model outputs transformed to have decision threshold at  $\Delta FP/\Delta TP = 2.0$  to compare different models.

## 8.3. Preparing the Data

The CRSS data is available [online at this link](#). The three main files for each year are Accident, Vehicle, and Person, and one uses the CASENUM and VEH\_NO fields to merge them into one dataset.

### 8.3.1. Order of Operations

To prepare the data we needed to do two things, to bin (discretize) some features and to impute missing data. We did not know which to do first, so we tested both ways using IVEware (Raghunathan, Solenberger, Berglund and van Hoewyk) for the imputation. The imputation is a stochastic process, and the difference between binning first and imputing first was as small as the difference between running twice with different random seeds. Since IVEware can

only handle up to about forty categories in each categorical field, we had had to bin some fields first either way, so we decided on binning first.

### 8.3.2. Binning

To bin a field's many categories into fewer categories, sometimes the meaning of the categories was a sufficient guide. In the HOSPITAL field, which we used as our target variable, we were only interested in two values, whether or not the person went to the hospital. The CRSS field has six values indicating how the person went to the hospital (ground ambulance, air ambulance, ...), and we merged those into one. For fields where the binning was not so obvious, we looked at how each value in the field correlates to hospitalization. We wanted to put AGE into bands, and looked to divide where the hospitalization rate changed. Interestingly, ages 16, 17, and 18 have lower hospitalization rates than ages below or above, so we put them into their own band. Around age 52 the hospitalization rate started to go up, so we split there. We binned other fields in a similar way.

The merging, dropping, and binning are all in the `CRSS_04_Discretize` code.

### 8.3.3. Imputing Missing Values

About 47% of the samples had unknown values in the thirty-eight fields we use for our analysis. The CRSS authors imputed unknown values in ten of those fields, another seventeen had no unknown values, but eleven fields we want to use had missing values that were not imputed by CRSS. The CRSS authors have a very helpful report on their imputation methods. (Herbert, 2019) The reasons why some fields get imputed include historical consistency going back to 1982.

(See `CRSS_04_5_Count_Missing_Values`)

When the CRSS authors imputed unknown values for a field, they published two fields, one with the imputed values and one with the values signifying "Unknown." We discarded the imputed fields and compared three methods for imputing missing values. Impute to Mode assigns to all missing values in a feature the most common value in that feature. IVEware: Imputation and Variance Estimation Software employs multivariate sequential regression, and is the method the CRSS authors used. Round Robin Random Forest, like in MissForest, was consistently the most accurate. We tested the methods by dropping all samples with missing values, randomly deleting (but keeping a copy of) fifteen percent of the known values, imputing, and comparing to the ground truth.

(See `CRSS_05_Impute_Random_Forest` for details.)

We did not address the question of incorrect data.

## 8.4. Selecting Features

We selected three groups of features to see whether more information would improve the model.

The first group of features held information that the police would already know before receiving a crash notification, like time of day, day of week, and urban/rural. A crash on a Saturday night in a rural area is far more likely to need an ambulance than one in a city at rush hour, so if no information specific to the crash is available, how well can we predict whether an ambulance is needed? We thought of this set of features as "easy" or "baseline."

The second group of features also included specific location and the age and sex of the primary user of the phone. Is the vehicle in an intersection or in a parking lot? Did the car end up off the roadway? What is the speed limit on that road? Getting that information from the latitude and longitude in the automated report would require instantaneous correlation with detailed maps. Whether such information significantly improves the model will inform whether policymakers should invest the time and effort to have that information available. We thought of this information as "medium" in cost.

The "hard" or "expensive" features would require regularly updated maps (work zones, lighting conditions), correlating records to guess which car the cell phone user is driving, and correlating multiple cell phone reports to count how many people are involved.

We dropped all crashes with a pedestrian, because unlike a tree or other vehicle, hitting a pedestrian may not cause the sudden deceleration that a cell phone could distinguish from sudden braking, so the cell phone likely would not register it as a crash.

(See `CRSS_06_Build_Model` for details.)

## 8.5. Handling Imbalanced Data

In our dataset only about fifteen percent of the people needed an ambulance. If a recommendation system never sent an ambulance, the model would have 85% accuracy, but be useless. Most algorithms for training models are designed

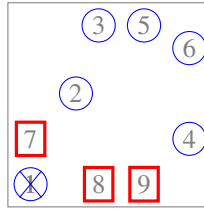
for balanced data, with half of the samples in each of the negative and positive classes. With an imbalanced data set we can address the imbalance in four levels: Resampling the dataset, modifying the loss function, choosing metrics other than accuracy, and using learning methods that account for the imbalance.

### 8.5.1. Resampling the Dataset

We can balance the dataset by undersampling the majority class (negative, “No ambulance”) or oversampling the minority class (positive, “Send Ambulance”). To balance by undersampling would mean throwing out eighty percent of the majority class, losing valuable information. A very popular method for oversampling is SMOTE (Synthetic Minority Oversampling TEchnique), which creates new minority samples between existing minority samples, but the “between” requires continuous data, and all of our data is discrete or categorical. What is between a Buick and a Volvo?

Tomek Links is one of the few resampling methods that works for categorical data. It is a selective undersampling method that removes majority samples that seem out of place. A Tomek Link is a majority/minority pair that are each others’ nearest neighbors, which was the case with about four percent of the majority samples. We used the Tomek algorithm to remove the majority sample of each Tomek link, undersampling the majority class, and then running it again to remove more that had not been Tomek links in the first undersampling run.

Consider this two-dimensional training dataset. The six blue circles represent samples (elements) of the majority negative class (“no ambulance”), and the three red squares represent the minority positive class (“ambulance”). Samples #7 and #1 are each others’ nearest neighbors of different classes, so they are Tomek Links and the algorithm deletes #1. In a second Tomek run, once #1 is gone, #7 and #2 are Tomek Links, so the method deletes #2.



Our original dataset has 619,027 samples. We first removed the 27,723 crashes involving a pedestrian, leaving 591,304 samples. Each sample had 82 features; we cut the number of features to 38 for our “Hard” features, then to 21 for “Medium,” and to 10 for “Easy.” We then split each of those three datasets 70/30 into a training set of 413,913 samples and a test set of 177,393 samples, preserving the proportions of negative and positive samples in both sets. We did the train/test split twice with different random seeds (“Round 1” and “Round 2”) to gauge how much of the small differences in results were due to stochasticity instead of differences in the model algorithms or hyperparameters. Tomek undersampling only applies to the training set, not to the test set.

We then ran Imbalanced-Learn’s TomekLinks algorithm, then ran it again on the results to give our “Tomek Once” and “Tomek Twice” undersampled datasets.

Hard Features, Round 1				Hard Features, Round 2			
	Samples	Change			Samples	Change	
Original	413,913			Original	413,913		
Tomek Once	399,515	14,398	3.48%	Tomek Once	399,714	14,199	3.43%
Tomek Twice	396,511	3,004	0.75%	Tomek Twice	396,718	2,996	0.75%
Total Change		17,402	4.23%	Total Change		17,195	4.18%

Medium Features, Round 1				Medium Features, Round 2			
	Samples	Change			Samples	Change	
Original	413,913			Original	413,913		
Tomek Once	406,691	7,222	1.74%	Tomek Once	406,781	7,132	1.72%
Tomek Twice	405,288	1,403	0.34%	Tomek Twice	405,368	1,413	0.35%
Total Change		8,625	2.08%	Total Change		8,545	2.07%



## Ambulance Dispatch

Easy Features, Round 1				Easy Features, Round 2			
	Samples	Change			Samples	Change	
Original	413,913			Original	413,913		
Tomek Once	413,909	4	0.00097%	Tomek Once	413,908	5	0.00121%
Tomek Twice	413,908	1	0.00024%	Tomek Twice	413,907	1	0.00024%
Total Change		5	0.00121%	Total Change		6	0.00145%

We ran the models on the two rounds of Tomek undersampled training for the Hard-feature and Medium-feature sets, not for the Easy because the undersampling was so small.

We were disappointed to not see a significant improvement in the model metrics from the undersampling; the difference between no undersampling, one runs of Tomek, and two runs turned out to be inconsequential, by which we mean that one approach was not consistently better when we ran the models with different random seeds.

### 8.5.2. Modifying the Loss Function

A popular and well established way to modify the loss function for imbalanced data is with class weights, which can have the same effect as naïve oversampling.

Three of our seven models take class weights, and for those we tried three different class weights. The Tomek undersampling changes the last weight slightly from 0.8499 to as low as 0.8433.

$\alpha$	Meaning
1/2	No class weight
2/3	$\Delta FP / \Delta TP < 2.0$ goal
0.85	Balanced classes

A related method is with focal loss, which has a modulating hyperparameter  $\gamma$  that increases the penalty for low-confidence samples. (Lin, Goyal, Girshick, He and Dollár, 2017) We tried five values of  $\gamma$ .

$\gamma$	Notes
0.0	Same as binary crossentropy
0.5	Very light modulation
1.0	Light modulation
2.0	Recommended by Lin
5.0	Heavy modulation

We did not see significant improvement using focal loss. (**Put in Label Reference**).

### 8.5.3. Metrics for Imbalance

In the [Metrics](#) subsection above we defined the metrics recall, precision, and f1. The most common metric in machine learning, the one that most algorithms are designed to maximize, is accuracy, the proportion of samples correctly classified. In that section's example of transformed model output, we had 150,107 out of 177,392 test samples correctly classified, giving 84.6% accuracy. Is that good? The model below, the raw results of the Logistic Regression model of the easy features set, recommends sending no ambulances, and it is correct in 150,771 of 177,392 test samples, giving 84.99% accuracy. Is that better?

Raw Model Output

ROC Curve

		Prediction	
		N	P
Actual	N	150,771	0
	P	26621	0
	0.8499	Accuracy	
	und	Precision	
	0.0	Recall	
	und	F1	
	0.659	AUC	

In this study, we have arbitrarily decided that we are willing to trade off up to two false positives to get one more true positive. Once we moved our decision thresholds to the ethical tradeoff point, the accuracy only varied from 0.836 to 0.854. The difference in accuracy tells us how many more (or fewer) false positives than true positives we have, with them being equal at 0.8499, and we get the same information from precision being less than, more than, or equal to 0.5. Therefore, we are not going to consider accuracy in evaluating our models.

#### 8.5.4. ML Algorithms for Imbalanced Data

[Expand this subsubsection]

- Random Undersampling Composite Models
- Bagging
- Boosting

#### 8.6. Models

We used seven binary classification algorithms. Three of them take class weights.

Model	Source	Class Weights
KerasClassifier with the Binary Focal Crossentropy loss function	Keras	Yes
Balanced Random Forest Classifier	Imbalanced-Learn	Yes
Balanced Bagging Classifier	Imbalanced-Learn	No
RUSBoost Classifier	Imbalanced-Learn	No
Easy Ensemble Classifier with AdaBoost Estimator	Imbalanced-Learn	No
Logistic Regression Classifier	Scikit-Learn	Yes
AdaBoost Classifier	Scikit-Learn	No

For the focal loss function, we tried seven different combinations of the hyperparameters  $\alpha$  for class weights and  $\gamma$  for penalty on badly misclassified samples. For the random forest and bagging models we tried three values of  $\alpha$ . Altogether we had seventeen model/hyperparameter combinations. We learned each of the seven models on datasets with the easy, medium, and hard features, and on the hard features we tested with Tomek undersampling 0, 1, and 2 times, for a total of five datasets, giving eighty-five model/hyperparameter/dataset combinations. We learned each of those sixty-five with two different random seeds, for a total of one hundred seventy results.

Seventeen Models			Seven Datasets				
Model	$\alpha$	$\gamma$	Features	Tomek			
Focal	1/2	0.0	Hard	None	Run twice with different random seeds	=	238 Sets of Results
Focal	2/3	0.0		Once			
Focal	2/3	0.5		Twice			
Focal	2/3	1.0		None			
Focal	2/3	2.0		Once			
Focal	2/3	5.0		Twice			
Focal	0.85	0.0		None			
Random Forest	1/2	×	Hard	Twice	×	Random seed 1	
Random Forest	2/3		Medium	None			
Random Forest	0.85		Medium	Once			
Bagging			Medium	Twice			
RUSBoost			Easy	None			
Easy Ens							
Log Reg	1/2						
Log Reg	2/3					Random seed 2	
Log Reg	0.85						
AdaBoost							

## 8.7. Analysis of Results

Our ML algorithms assign to each sample (feature vector, crash person) a probability  $p \in [0, 1]$  that the person needs an ambulance. The histogram below left shows the percentage of the dataset in each range of  $p$ , showing the percentages for the negative class (“Does not need an ambulance”) and the positive class (“Needs an ambulance”). On the right, the Receiver Operating Characteristic (ROC) curve, and particularly the area under the curve (AUC), is a metric for how well the model separates the two classes, with  $AUC = 1.0$  being perfect and  $AUC = 0.5$  (the dashed line) being just random assignment with no insight.

We would love to have results like in the graphs below, where the machine learning (ML) algorithm nearly perfectly separates the two classes. There is some overlap between  $p = 0.6$  and  $p = 0.8$  with some samples the algorithm misclassifies, but the model clearly separates most samples. Having an AUC of 0.996 would be amazing.

[Put in BRFC\_Hard\_alpha\_0\_5\_Train\_Pred\_Wide.pgf once we have it.)

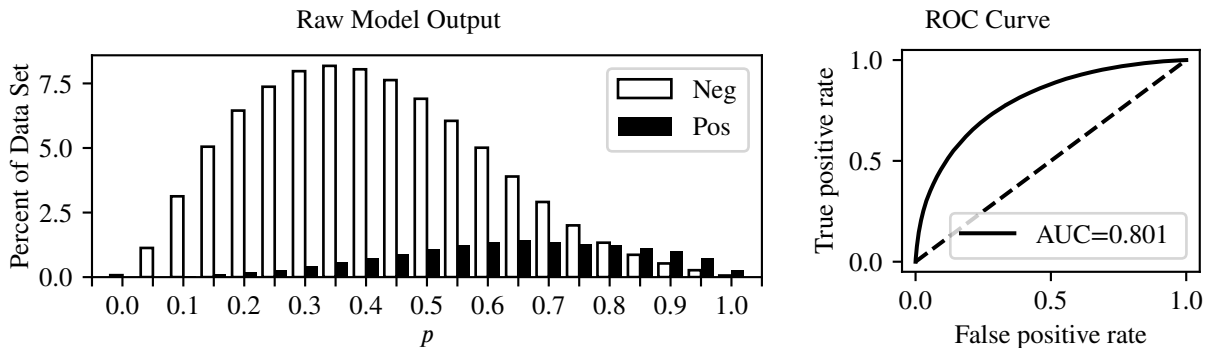
Unfortunately, our test results do not look quite that nice. They do not separate the two classes as well. Some distributions are clustered to one side or in the middle. Some models give the results in  $p \in [0, 1]$  rounded to two decimal places so that we cannot hope for a level of detail beyond that, and one algorithm, Bagging, gives  $p$  rounded to only one decimal place.

Let us look at some examples. In all of them, AUC is in the range  $[0.7, 0.8]$ , so the various models separate the positive and negative classes about equally well overall, with none being dramatically better or worse. We will later show how we investigated which models do a better job in the ranges of interest.

BRFC\_5\_Fold\_alpha\_0\_5\_Hard\_Test

This model does not separate the negative and positive classes as well as the ideal, giving a much lower AUC (area under the ROC curve). These results are actually from the same model as the ideal above, but the ideal are the results on the training set and below on the test set, showing overfitting.

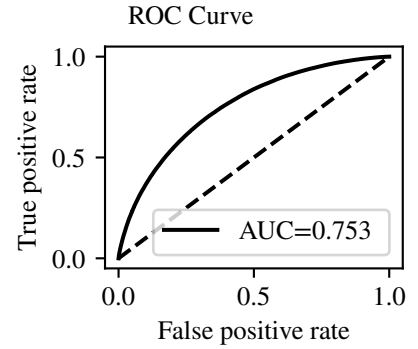
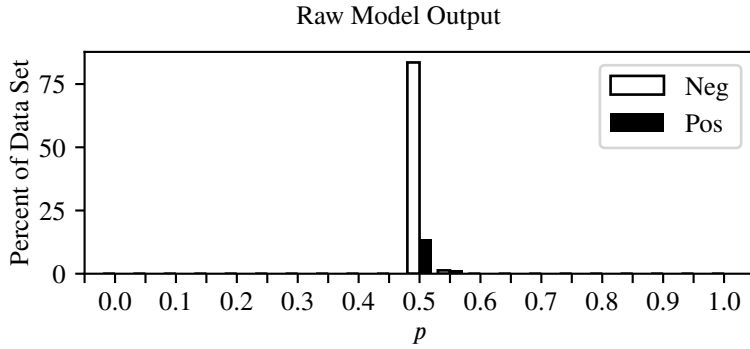
In these results, the 100 most frequent values comprised 93% of the results, meaning that, while there is some noise making the distribution look continuous, it is mostly discrete to two decimal places, so we cannot hope for fine detail in tuning the decision threshold.



AdaBoost\_5\_Fold\_Hard\_Test

In this model the values are clustered very tightly, but in that small range the 214,070 samples return 210,442 different values of  $p$ , so there is much diversity that we can't see in this representation.

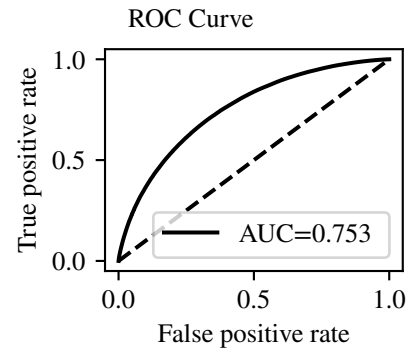
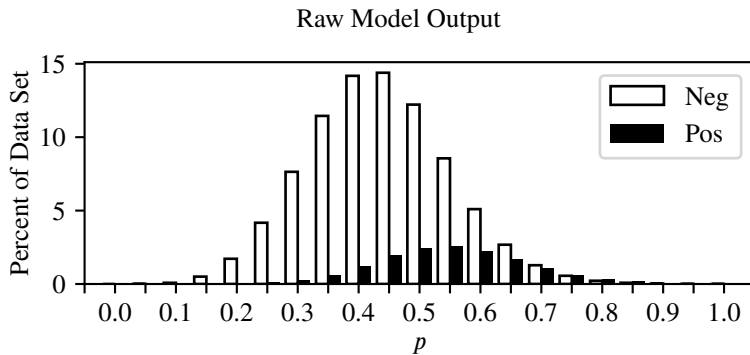
AdaBoost\_5\_Fold\_Hard\_Test



In this work we used two methods to give the results of different models similar distributions. This case illustrates directly transforming the  $y_{proba}$  values.

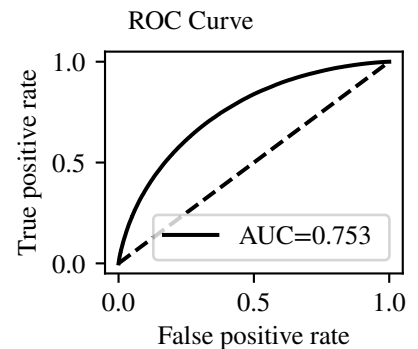
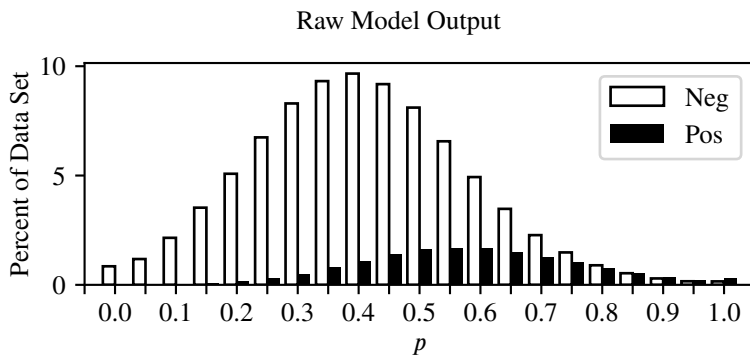
To make a useful visualization of the results where we can see the interplay between the negative and positive classes, we can transform the data. A transformation that preserves rank will have no effect on the ROC curve. [Cite] For the graph below, we mapped the smallest value in the set to 0 and the largest to 1.

AdaBoost\_5\_Fold\_Hard\_Test\_Transformed\_100



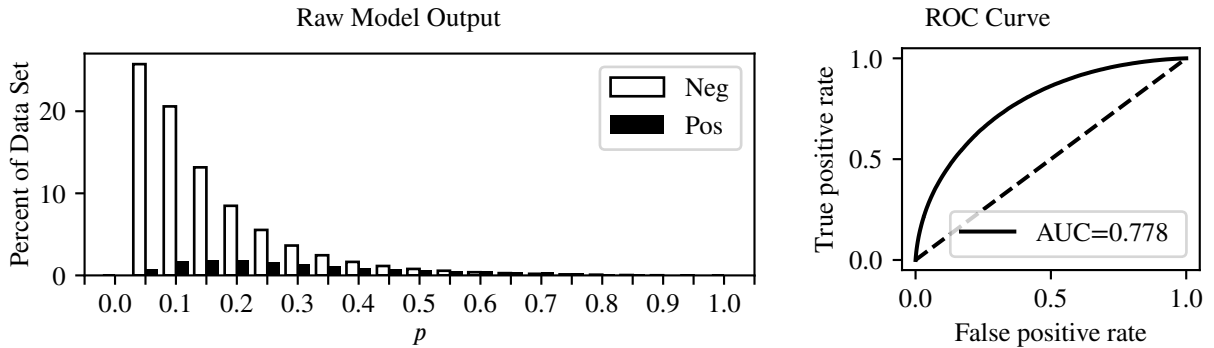
The distribution has long tails, so we can make a more useful visualization by truncating the ends. For this graph we mapped the 0.01 quantile to 0 and the 0.99 quantile to 1 leaving the center 98% of the distribution and truncated the ends. Our goal in clipping the tails is to make all of the models' results have approximately the same granularity when we choose the decision thresholds that give us the (politically) desired results.

AdaBoost\_5\_Fold\_Hard\_Test\_Transformed\_98



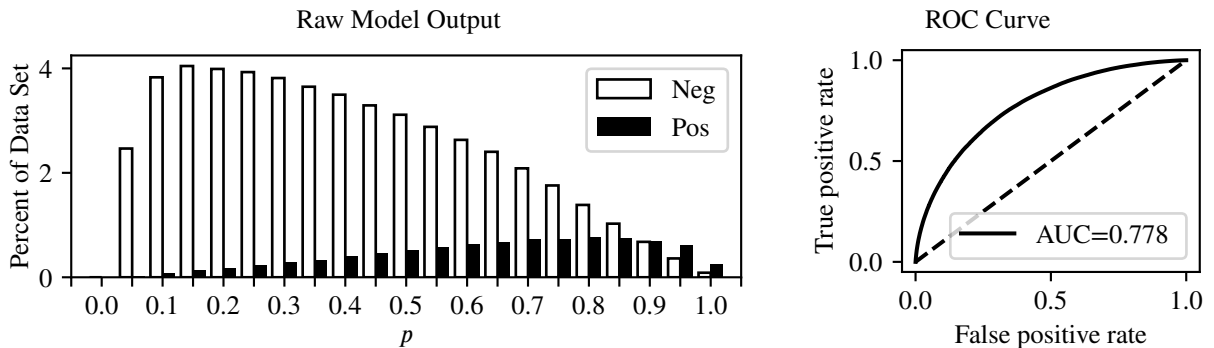
The model below is as effective at separating the two classes (ROC = 0.778), but the distribution is skewed to the left. Its results were nearly continuous, with the 214,070 samples returning 210,157 unique values of  $p$ , so we can fine tune the decision threshold.

KBFC\_5\_Fold\_alpha\_0\_5\_gamma\_0\_0\_Hard\_Test



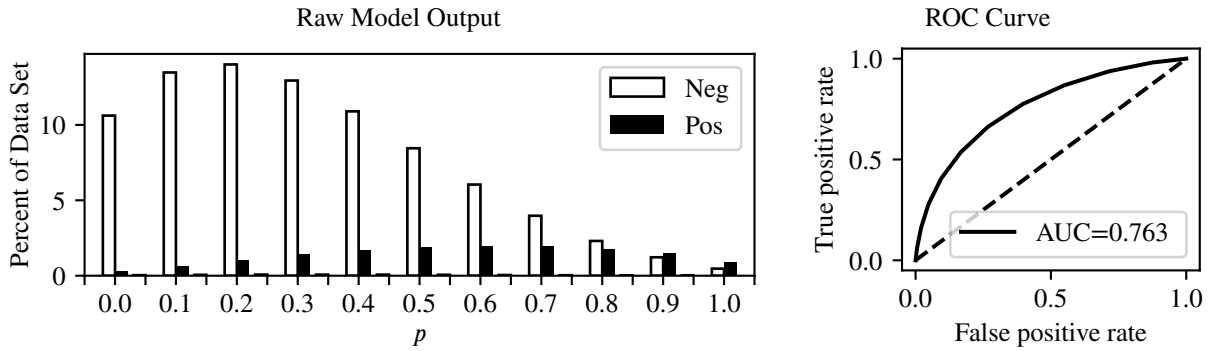
The second method we will use to modify the model outputs' distribution is to employ class weights in the model building process. Here we employed class weights proportional to the class imbalance. The motivation behind class weights is to better separate the positive and negative classes, but note that the area under the ROC curve does not change. We have not investigated whether the model using class weights does a better job at separating the classes in some intervals, but overall the effect is negligible. One effect using class weights did have here is shifting the distribution.

KBFC\_5\_Fold\_alpha\_balanced\_gamma\_0\_0\_Hard



Bagging\_Hard\_Tomek\_0\_v1\_Test

This model returned 217 different values, but most of them were rare. Taking out the 5% of the data set with the least frequent values, 95% of the samples had only 10 values of  $p$ . It may be a useful model, but we will not be able to fine tune the decision threshold.



Other stuff

## 9. Results

## 10. Conclusions

## 11. Discussion

## 12. Future Work

## 13. To Do, Notes to Self

(Ma, Xie, Chen, Qiao and Li, 2023) uses AdaCost, and uses smartphones to collect vehicle kinematic data in field tests. It's the only article in TRpC that uses AdaCost.

## 14. Henry\_07\_22\_23

## 15. To Henry, 22 July 2023

Henry,

Greetings from Frankfurt! And later in the writing process, Barcelona!

I think I've found something that works for building and interpreting a model in a way that's actually useful in the political settings where these decisions are made.

The analysis all builds on moving the decision threshold from the default  $p = 0.5$  to a value of  $p$  that gives you the tradeoff the political process chooses. I haven't seen this done much, and I don't know whether there are good reasons to not do it.

I haven't found such an approach in the crash analysis literature, particularly using the slope of the ROC curve (or something equivalent to it). There are three possibilities.

1. I haven't looked hard enough.
2. I've found something new, at least in the application.
3. The thing I'm doing doesn't work.

### 15.1. Big Question

I think that whether my analysis works hinges on this question.

Once you've built a binary classification model on the training set and evaluate it on the test set, the model returns for each sample in the test set a value  $p$  that I've been told gives the probability that the sample is in the positive class. Then you analyze the model by picking a decision threshold  $\theta$  and seeing how many elements of the positive and negative classes have values of  $p$  on the correct side of  $\theta$ .

The value of  $p$  isn't exactly the probability, but my analysis hinges on this conjecture.

1. If a model gives two samples the same value of  $p$ , then the model says that those two samples have the same probability of being in the positive class.
2. Probability is an increasing function of  $p$ : If a model gives samples  $a$  and  $b$  values  $p_a$  and  $p_b$  with  $p_a < p_b$ , then, according to the model, sample  $b$  has a higher probability of being in the positive class than sample  $a$ .

I would appreciate your thoughts and direction.

Thanks,

Brad

## 15.2. Scenario

The scenario is that the emergency dispatchers receive an automated crash notification from a cell phone and have yet not received a call from an eyewitness. The dispatchers do not know with strong certainty whether an ambulance is needed, but they have some indicators. The dispatchers have three options.

**Always** Always send an ambulance immediately to all such notifications, knowing that only about 15% will be needed.

**Wait** Dispatch police, but wait for a report from an eyewitness (perhaps the police) before sending an ambulance.

**Sometimes** Use a machine learning model with some decision threshold to decide which crashes to send an ambulance to immediately, reserving the option to send an ambulance later based on an eyewitness report.

## 15.3. Decision Threshold

Here's something new from my last email.

How to determine the decision threshold is a political decision, not a technical one. We will consider three ways politicians might answer that question and how to implement each in our models and decision thresholds.

1. Our local fleet of ambulances now goes to  $n$  crashes per year. In the short term, without buying more ambulances and hiring more teams, we can increase the number of ambulance runs to crashes by some percentage, or in the longer term we are willing to increase the number of ambulances going to crashes by a larger, but still fixed, percentage.

We will use 5% as our example of how to implement this policy. The increase does not include the true positives (TP), because those ambulances would go anyway; the increase is the allowable number of false positives (FP). Set the decision threshold where the number of false positives is 5% of the positive class ( $P = FN + TP$ ).

$$\frac{FP}{P} = \frac{FP}{FN + TP} = 0.05$$

Lots of ratios of TN, FP, FN, and TP have names, but I haven't found a name for  $FP/P$  or where other people have used it.

2. We are willing to send ambulances based on automated crash reports, but only up to the point where a certain proportion of the ambulances we immediately dispatch ( $FP+TP$ ) are actually needed (TP), which is equivalent to saying that we are willing to immediately send a certain number of unneeded ambulances for each one we automatically send that is needed.

This is what I was trying to get at with FP and TP, but I realized it's equivalent to Precision, which the readers will understand.

Choose the decision threshold where the precision is the specified level. We will use 1/3 for our example, being willing to send two FP for each TP.

3. By looking at the slope of the ROC curve we can (roughly) estimate the probability that a particular crash needs an ambulance. Some of them almost definitely need an ambulance, and we should dispatch those immediately, but we will choose a minimum probability to which we will immediately dispatch an ambulance.

I'm going to use 50% as an example of the minimum probability. The model assigns to each sample in the test set at value  $p \in [0, 1]$ . I had read that  $p$  was the probability that the sample was in the positive class, but I don't think that's exactly true. What is true is that  $p$  generally increases with probability.

In each sufficiently large\* range of  $p$  (like  $p \in [0.60, 0.61]$ ) there are some number of elements of the negative and positive class. For a given range of  $p$ , call the number of elements of the negative class "Neg" and the number of elements of the positive class "Pos." For the samples in that range of  $p$ , the probability that they are in the positive class is

$$\frac{\text{Pos}}{\text{Pos} + \text{Neg}}$$

This expression is proportional to the slope of the ROC curve at that value of  $p$ .

I want to call this "marginal precision," but I haven't seen that term used that way in the ML literature. I think "marginal precision" means something else in statistics. See that

$$\text{Pos} = \frac{\Delta \text{TP}}{\Delta p}, \quad \text{Neg} = \frac{\Delta \text{FP}}{\Delta p}, \quad \text{and} \quad \text{Pos} + \text{Neg} = \frac{\Delta(\text{TP} + \text{FP})}{\Delta p}, \quad \text{so} \quad \frac{\text{Pos}}{\text{Pos} + \text{Neg}} = \frac{\Delta \text{TP}}{\Delta(\text{TP} + \text{FP})}$$

\*We have two challenges with choosing  $\Delta p$ , the size of our range of  $p$ , which we would like to be really small. One is that some of our ML algorithms return (almost all) values of  $p$  rounded to two decimal places, so we can't get more precision than that. One of my algorithms (Balanced Bagging) gives  $p$  for each sample to only one decimal place; thus, "sufficiently large" depends on the algorithm.

The other problem is that if you zoom in too close, the number of samples in each  $\Delta p$  isn't large enough to compensate for the randomness, and you see that your "curve" is actually jagged. Because I wanted more samples in my test set, I went from using a 70/30 train/test split to using 5-fold validation, where all of the samples are in a test set.

## 15.4. Understanding the Data

### 15.4.1. Total Effects

The confusion matrix gives the totals based on the model and choice of decision threshold.

		Predicted	
		PP	PN
Actual	P	TP	FN
	N	FP	TN



## Ambulance Dispatch

P	Number of crash persons who need an ambulance, also the number to whom we will <i>immediately or eventually</i> send an ambulance
N	Number of crash person who do not need an ambulance
PP	Number of crash persons to whom we immediately dispatch an ambulance
PN	Number of crash persons to whom we do not <i>immediately</i> dispatch an ambulance
TP	Number of crash persons to whom we send a needed ambulance
FN	Number of crash persons who need an ambulance, but to whom we do not <i>immediately</i> send one, but we will send one later
FP	Number of crash persons to whom we dispatch an ambulance that is not needed
TN	Number of crash persons who do not need an ambulance and to whom we do not immediately (or ever) send one

$\frac{TP}{FP + TP} = \frac{TP}{PP}$	Precision, the proportion of immediately dispatched ambulances that are needed
$\frac{TP}{FN + TP} = \frac{TP}{P}$	Accuracy, the proportion of crash persons needing an ambulance to whom we immediately dispatch one
$\frac{FP}{FN + TP} = \frac{FP}{P}$	Proportion of increase in number of ambulances sent because of immediate dispatch. The P number of ambulances would have been dispatched anyway, but now the FP number of ambulances are also being sent.

### 15.4.2. Marginal Effects of Moving the Decision Threshold

What if we move the decision threshold from  $\theta = 0.85$  to  $\theta = 0.86$ ? What would the marginal effect be?

p	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.80	1,392	1,585	0.53	589,317	11,498	90,351	22,400	0.66	0.20	0.10	0.05
0.81	1,358	1,673	0.55	590,675	10,140	92,024	20,727	0.67	0.18	0.09	0.04
0.82	1,244	1,590	0.56	591,919	8,896	93,614	19,137	0.68	0.17	0.08	0.04
0.83	1,112	1,560	0.58	593,031	7,784	95,174	17,577	0.69	0.16	0.07	0.04
0.84	972	1,594	0.62	594,003	6,812	96,768	15,983	0.70	0.14	0.06	0.03
0.85	952	1,479	0.61	594,955	5,860	98,247	14,504	0.71	0.13	0.05	0.03
0.86	886	1,489	0.63	595,841	4,974	99,736	13,015	0.72	0.12	0.04	0.03
0.87	712	1,481	0.68	596,553	4,262	101,217	11,534	0.73	0.10	0.04	0.02
0.88	731	1,429	0.66	597,284	3,531	102,646	10,105	0.74	0.09	0.03	0.02
0.89	622	1,389	0.69	597,906	2,909	104,035	8,716	0.75	0.08	0.03	0.02
0.90	565	1,357	0.71	598,471	2,344	105,392	7,359	0.76	0.07	0.02	0.01

p		Value returned by the model for each sample (crash person), a proxy for the probability that the sample is in the positive class (crash person needs an ambulance). It is not exactly the probability, but it increases with the probability.
$\Delta p$	0.01	Width of each band of p. For the above model, we can't go smaller because almost all of the returned $p$ values are rounded to two decimal places. In some models the values of $p$ are more continuous, so we could go with smaller $\Delta p$ , but if we go too small, the randomness inherent in the algorithm would make the results not smooth.
Neg	1,479	The number of additional unneeded ambulances we would send if we changed $p$ from 0.86 to 0.85 The number of actual negative samples in this band of $p$

## Ambulance Dispatch

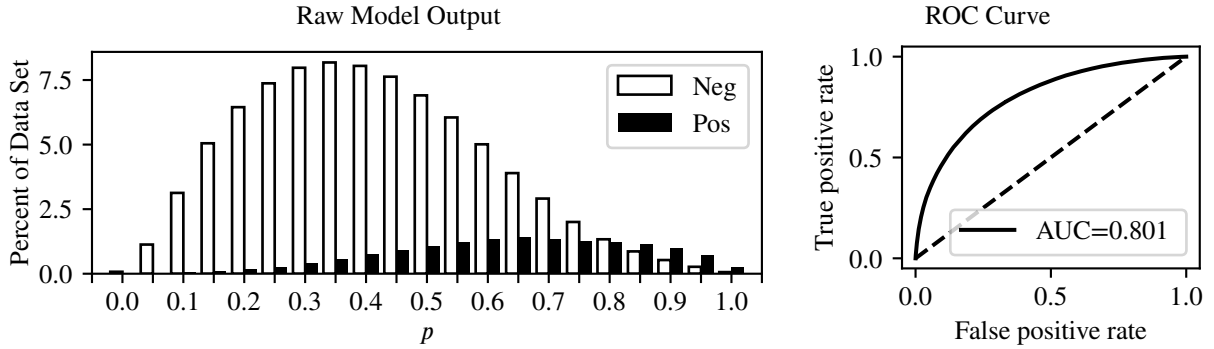
$\text{mPrec} = \frac{\text{Pos}}{\text{Neg} + \text{Pos}}$	Pos	952	The number of additional needed ambulances we would send if we changed $p$ from 0.86 to 0.85 The number of actual positive samples in this band of $p$
		0.61	61% of the <i>additional</i> ambulances we are sending (because we moved $p$ from 0.86 to 0.85) that are needed “Marginal Precision”  All of the ambulances we are immediately dispatching have <i>at least</i> a 61% chance of being needed
	TN	594,955	If we choose $p = 0.85$ , then we will correctly decide that these 594,955 people do not need an ambulance, immediately or at all. Running total of Neg from $p = 0$
	FP	5,860	If we choose $p = 0.85$ , then we will immediately dispatch 5,860 unneeded ambulances Reverse running total of Neg from $p = 1.00$
	FN	98,247	If we choose $p = 0.85$ , then we will not <i>immediately</i> send ambulances to these 98,247 people, but will dispatch them when we hear from an eyewitness that an ambulance is needed Running total of Pos from $p = 0$
	TP	14,504	If we choose $p = 0.85$ , then we will immediately dispatch these 14,504 ambulances Running reverse total of Pos from $p = 1.00$
	FP/P	0.05	By choosing $p = 0.85$ , we will send 5% more ambulances than if we did not dispatch any ambulances. This number shows the increased cost of ambulance service.
$\hat{p} = \frac{\text{PP}}{\text{PN} + \text{PP}}$		0.03	Proportion of crash persons to whom we are immediately dispatching an ambulance. I think Henry said that, usually, we want $\hat{p}$ to be the same as the proportion of crash persons who need an ambulance, $P/(N + P)$ , which I think is equivalent to saying that $\text{FP} = \text{FN}$ . I’m pretty sure that’s not what we want in this application.

### 15.5. Evaluating Models

The politicians’ choice of options above determine where we set the decision threshold for each model. Choosing between models is then easy: Choose the model that yields the largest number of true positives (maximizes TP), which is the one that maximizes recall, because  $\text{Recall} = \text{TP}/P$ , and the number of positive samples is the same in all of the models we’re building.

### 15.6. Example: Finding Decision Thresholds in One Model

Here’s a histogram of the  $p$  values of the elements of the negative and positive classes for one model, the Balanced Random Forest Classifier with no class weights, on the full-feature (“Hard”) dataset that includes relevant information that may or may not be available in real time. This model doesn’t do a great job of separating the positive and negative classes, but it’s better than random.



Here's a table of the same data with  $\Delta p = 0.05$ . With the output from this model we can go as small as  $\Delta p = 0.01$ , but that would take several pages to show. I will zoom in on parts of the table below.

$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	617	2	0.00	617	600,198	2	112,749	0.16	1.00	5.32	1.00
0.05	8,421	69	0.01	9,038	591,777	71	112,680	0.16	1.00	5.25	0.99
0.10	21,762	308	0.01	30,800	570,015	379	112,372	0.16	1.00	5.06	0.96
0.15	34,768	625	0.02	65,568	535,247	1,004	111,747	0.17	0.99	4.75	0.91
0.20	45,253	1,271	0.03	110,821	489,994	2,275	110,476	0.18	0.98	4.35	0.84
0.25	52,539	2,041	0.04	163,360	437,455	4,316	108,435	0.20	0.96	3.88	0.77
0.30	57,103	3,074	0.05	220,463	380,352	7,390	105,361	0.22	0.93	3.37	0.68
0.35	59,125	4,177	0.07	279,588	321,227	11,567	101,184	0.24	0.90	2.85	0.59
0.40	57,636	5,410	0.09	337,224	263,591	16,977	95,774	0.27	0.85	2.34	0.50
0.45	54,781	6,860	0.11	392,005	208,810	23,837	88,914	0.30	0.79	1.85	0.42
0.50	48,984	7,956	0.14	440,989	159,826	31,793	80,958	0.34	0.72	1.42	0.34
0.55	42,326	8,998	0.18	483,315	117,500	40,791	71,960	0.38	0.64	1.04	0.27
0.60	34,742	10,006	0.22	518,057	82,758	50,797	61,954	0.43	0.55	0.73	0.20
0.65	27,178	10,132	0.27	545,235	55,580	60,929	51,822	0.48	0.46	0.49	0.15
0.70	20,014	9,991	0.33	565,249	35,566	70,920	41,831	0.54	0.37	0.32	0.11
0.75	13,935	9,409	0.40	579,184	21,631	80,329	32,422	0.60	0.29	0.19	0.08
0.80	9,356	8,739	0.48	588,540	12,275	89,068	23,683	0.66	0.21	0.11	0.05
0.85	6,131	8,400	0.58	594,671	6,144	97,468	15,283	0.71	0.14	0.05	0.03
0.90	3,687	7,562	0.67	598,358	2,457	105,030	7,721	0.76	0.07	0.02	0.01
0.95	1,968	5,691	0.74	600,326	489	110,721	2,030	0.81	0.02	0.00	0.00
1.00	489	2,030	0.81	600,815	0	112,751	0	nan	0.00	0.00	0.00

## 15.7. Answers to Political Questions for This Model

1. Send up to 5% more ambulances.

p	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.80	1,392	1,585	0.53	589,317	11,498	90,351	22,400	0.66	0.20	0.10	0.05
0.81	1,358	1,673	0.55	590,675	10,140	92,024	20,727	0.67	0.18	0.09	0.04
0.82	1,244	1,590	0.56	591,919	8,896	93,614	19,137	0.68	0.17	0.08	0.04
0.83	1,112	1,560	0.58	593,031	7,784	95,174	17,577	0.69	0.16	0.07	0.04
0.84	972	1,594	0.62	594,003	6,812	96,768	15,983	0.70	0.14	0.06	0.03
<b>0.85</b>	952	1,479	<b>0.61</b>	594,955	5,860	98,247	14,504	<b>0.71</b>	<b>0.13</b>	<b>0.05</b>	0.03
0.86	886	1,489	0.63	595,841	4,974	99,736	13,015	0.72	0.12	0.04	0.03
0.87	712	1,481	0.68	596,553	4,262	101,217	11,534	0.73	0.10	0.04	0.02
0.88	731	1,429	0.66	597,284	3,531	102,646	10,105	0.74	0.09	0.03	0.02
0.89	622	1,389	0.69	597,906	2,909	104,035	8,716	0.75	0.08	0.03	0.02
0.90	565	1,357	0.71	598,471	2,344	105,392	7,359	0.76	0.07	0.02	0.01

At  $p = 0.85$  we get  $FP/P = 0.05$ , so if we immediately dispatched ambulances to crashes the model predicts with  $p > 0.85$ , we would increase the load on our ambulance fleet by the allowed 5%. At this decision threshold,

- Recall = 0.13, so we would be immediately dispatching ambulances to 13% of the people who need one.
- Precision = 0.71, so 71% of the ambulances we immediately dispatched would be needed, and
- mPrec = 0.61, so each ambulance we immediately dispatched would have at least a 61% chance of being needed.

2. **Immediately dispatch a total of two unneeded ambulances for each needed ambulance, i.e. Precision =  $1/(2+1) = 1/3$ .**

p	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.41	10,889	1,438	0.12	370,854	229,961	21,063	91,688	0.29	0.81	2.04	0.45
0.42	10,778	1,476	0.12	381,632	219,183	22,539	90,212	0.29	0.80	1.94	0.43
0.43	10,541	1,504	0.12	392,173	208,642	24,043	88,708	0.30	0.79	1.85	0.42
0.44	10,283	1,455	0.12	402,456	198,359	25,498	87,253	0.31	0.77	1.76	0.40
0.45	10,095	1,622	0.14	412,551	188,264	27,120	85,631	0.31	0.76	1.67	0.38
0.46	9,770	1,592	0.14	422,321	178,494	28,712	84,039	0.32	0.75	1.58	0.37
<b>0.47</b>	9,459	1,650	<b>0.15</b>	431,780	169,035	30,362	82,389	<b>0.33</b>	<b>0.73</b>	<b>1.50</b>	0.35
0.48	9,164	1,770	0.16	440,944	159,871	32,132	80,619	0.34	0.72	1.42	0.34
0.49	8,761	1,716	0.16	449,705	151,110	33,848	78,903	0.34	0.70	1.34	0.32
0.50	8,578	1,787	0.17	458,283	142,532	35,635	77,116	0.35	0.68	1.26	0.31
0.51	8,255	1,787	0.18	466,538	134,277	37,422	75,329	0.36	0.67	1.19	0.29
0.52	7,940	1,871	0.19	474,478	126,337	39,293	73,458	0.37	0.65	1.12	0.28

At  $p = 0.47$  we get Precision = 0.33, which fits our political constraints. Also at this decision threshold,

- Recall = 0.73, so we would be immediately dispatching ambulances to 73% of the people who need one.
- mPrec = 0.61, so each ambulance we immediately dispatched would have at least a 61% chance of being needed.
- $FP/P = 1.50$ , so we would increase the number of ambulances being sent by 150%, which may not be possible in the short run and too expensive in the long run.

The political decision makers may choose to stay with this Precision metric but change it to something less expensive like Precision = 0.5, and with the data we have we could tell them the implications of that decision.

3. **Immediately dispatch ambulances to crashes with at least a 50% probability of needing one.**

p	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.73	2,295	1,749	0.43	576,458	24,357	78,787	33,964	0.58	0.30	0.22	0.08
0.74	2,311	1,696	0.42	578,769	22,046	80,483	32,268	0.59	0.29	0.20	0.08
0.75	2,125	1,672	0.44	580,894	19,921	82,155	30,596	0.61	0.27	0.18	0.07
0.76	1,993	1,653	0.45	582,887	17,928	83,808	28,943	0.62	0.26	0.16	0.07
0.77	1,859	1,640	0.47	584,746	16,069	85,448	27,303	0.63	0.24	0.14	0.06
<b>0.78</b>	1,656	1,717	<b>0.51</b>	586,402	14,413	87,165	25,586	<b>0.64</b>	<b>0.23</b>	<b>0.13</b>	0.06
0.79	1,523	1,601	0.51	587,925	12,890	88,766	23,985	0.65	0.21	0.11	0.05
0.80	1,392	1,585	0.53	589,317	11,498	90,351	22,400	0.66	0.20	0.10	0.05
0.81	1,358	1,673	0.55	590,675	10,140	92,024	20,727	0.67	0.18	0.09	0.04
0.82	1,244	1,590	0.56	591,919	8,896	93,614	19,137	0.68	0.17	0.08	0.04

A crash report with  $p = 0.78$  has a mPrec = 51% chance of needing an ambulance, and crashes with  $p > 0.78$  have a higher chance, so immediately dispatch ambulances to crash reports with  $p > 0.78$ . Also at this decision threshold,

- Recall = 0.23, so we would be immediately dispatching ambulances to 23% of the people who need one.
- Prec = 0.64, so the ambulances we immediately dispatched would have at least a 64% chance of being needed.
- FP/P = 0.13, so we would increase the number of ambulances being sent by 13%.

In this case we would like to dig further into the data to see more precisely where in  $p \in (0.77, 0.78)$  the value of mPrec is closest to 0.50, but except for some noise, this model only returns values of  $p$  to two decimal places. In this model, only 8% of the non-unique values of  $p$  have more than two places of precision. If we tried to dig deeper we would be looking at really small counts and see more randomness than actual insight.

## 15.8. Comparing Models

In all of these comparisons the Balanced Random Forest Classifier (BRFC) is clearly best, but I did not spend much time optimizing the models or test other algorithms. Mainly what I'm doing here is showing how I would compare the algorithms.

### 1. Send up to 5% more ambulances, i.e. FP/P = 0.05

Model	p	mPrec	Prec	Rec	FP/P
BRFC	0.88	0.62	0.71	0.13	0.05
KBFC	0.76	0.57	0.68	0.11	0.05
OBFC	0.57	0.57	0.67	0.11	0.05
AdaBoost	0.71	0.52	0.57	0.07	0.05
RUSBoost	0.72	0.49	0.58	0.07	0.05
LogReg	0.6	0.51	0.59	0.07	0.05
BalBag	0.9	0.56	0.68	0.07	0.03
EEC	0.84	0.49	0.52	0.06	0.05

### 2. Immediately dispatch a total of two unneeded ambulances for each needed ambulance, i.e. Precision = $1/(2+1) = 1/3$ .

Model	p	mPrec	Prec	Rec	FP/P
BRFC	0.5	0.16	0.34	0.72	1.42
BalBag	0.48	0.17	0.32	0.66	1.41
KBFC	0.21	0.18	0.33	0.65	1.33
OBFC	0.26	0.18	0.33	0.65	1.32
LogReg	0.56	0.21	0.33	0.57	1.16
AdaBoost	0.51	0.2	0.33	0.57	1.14
RUSBoost	0.51	0.21	0.33	0.56	1.12
EEC	0.51	0.19	0.33	0.49	0.97

3. **Immediately dispatch ambulances to crashes with at least a 50% probability of needing one, i.e. mPrec = 0.50**

Model	p	mPrec	Prec	Rec	FP/P
BRFC	0.78	0.5	0.64	0.23	0.13
KBFC	0.88	0.48	0.6	0.18	0.12
BalBag	0.88	0.49	0.6	0.16	0.11
OBFC	0.5	0.5	0.62	0.16	0.1
AdaBoost	0.8	0.5	0.56	0.08	0.07
LogReg	0.54	0.5	0.58	0.08	0.06
RUSBoost	0.87	0.5	0.57	0.08	0.06
EEC	0.92	0.5	0.52	0.06	0.05

### 15.9. Comparing Models over Three Sets of Features

I ran the models on three sets of features. You can think of them as “Easy, Medium, and Hard” or “Cheap, Moderate, and Expensive.”

**Easy** The Easy features are the information the dispatchers already have (including time of day, day of week, weather) plus a bit of information from the location (like whether it’s on an interstate highway).

**Medium** The Medium features add more detailed information about the location (like whether it’s at an intersection or a parking lot) and a bit about the user of the phone (like age and sex).

**Hard** The Hard features add really detailed information about the location (like whether it’s in a work zone), correlates phone user information from the cell service provider with government and insurance records on vehicle ownership to guess at the kind of vehicle involved, and correlates multiple simultaneous notifications from the same location to guess at the number of people involved and whether it’s a school bus. Getting the “hard” features may also pose privacy issues.

Political decision makers can use the differences in the model results to decide whether to invest in the infrastructure to get the more expensive levels of data in real time.

Future work could give better detail by going through each feature, ranking how much it would cost to get that data and how much that feature would contribute to the quality of the model.

1. **Send up to 5% more ambulances, i.e. FP/P = 0.05**

Features	Model	p	mPrec	Prec	Rec	FP/P
Easy	BRFC	0.96	0.36	0.43	0.05	0.06
Medium	BRFC	0.91	0.5	0.57	0.07	0.05
Hard	BRFC	0.88	0.62	0.71	0.13	0.05

Recall goes from 5% to 13% of needed ambulances being dispatched immediately.

2. **Immediately dispatch a total of two unneeded ambulances for each needed ambulance, *i.e.* Precision =  $1/(2+1) = 1/3$ .**

Features	Model	p	mPrec	Prec	Rec	FP/P
Easy	BRFC	0.79	0.28	0.33	0.2	0.41
Medium	BRFC	0.59	0.21	0.33	0.51	1.02
Hard	BRFC	0.5	0.16	0.34	0.72	1.42

Recall goes from 20% to 72% of needed ambulances being dispatched immediately, but with the total number of ambulances being sent to crashes increasing 40% to 142%, which may not be possible in the budgeting process.

3. **Immediately dispatch ambulances to crashes with at least a 50% probability of needing one, *i.e.* mPrec = 0.50**

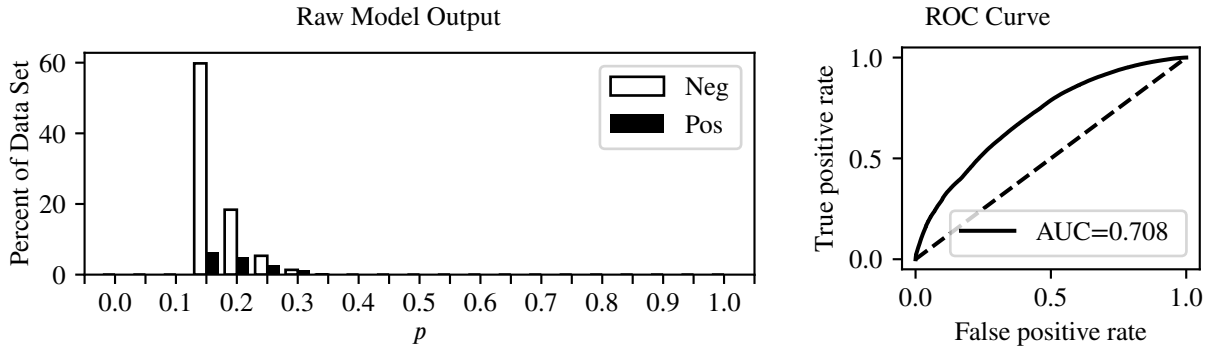
Features	Model	p	mPrec	Prec	Rec	FP/P
Easy	EEC	0.83	0.44	0.32	0.07	0.15
Medium	KBFC	0.73	0.5	0.54	0.08	0.07
Hard	BRFC	0.78	0.5	0.64	0.23	0.13

Recall goes from 7% to 23% of needed ambulances being dispatched immediately. Going from Easy to Medium does not significantly increase the recall, but it does decrease the ambulance cost, with the percentage of additional ambulances being sent to crashes going from 15% to 7%.

## 16. Results

## 16.1. Hard Features

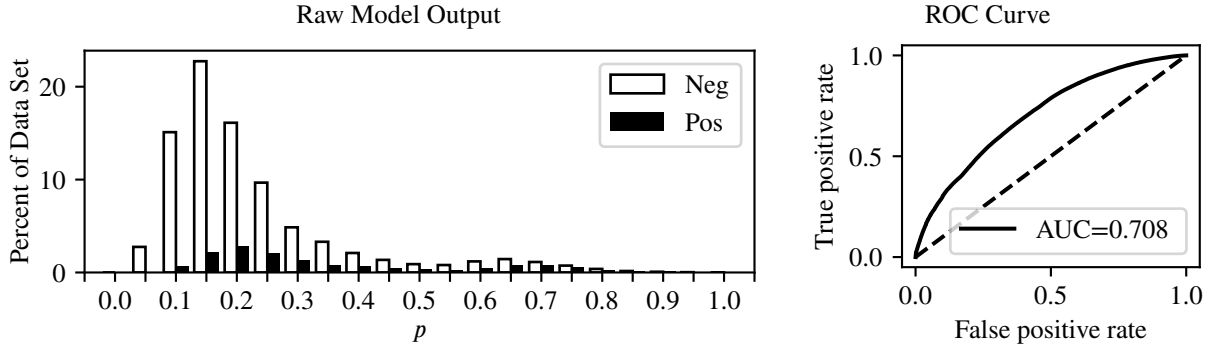
RFC\_5\_Fold\_Hard\_Test



$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.05	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.10	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.15	426,730	45,467	0.10	426,730	178,880	45,467	62,489	0.26	0.58	1.66	0.34
0.20	131,150	34,651	0.21	557,880	47,730	80,118	27,838	0.37	0.26	0.44	0.11
0.25	38,027	18,905	0.33	595,907	9,703	99,023	8,933	0.48	0.08	0.09	0.03
0.30	9,648	8,717	0.47	605,555	55	107,740	216	0.80	0.00	0.00	0.00
0.35	55	216	0.80	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.40	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.45	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.50	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.55	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.60	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.65	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.70	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.75	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.80	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.85	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.90	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.95	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
1.00	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00

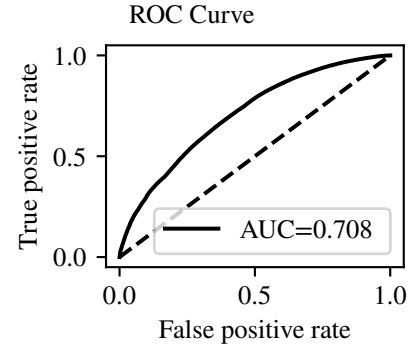
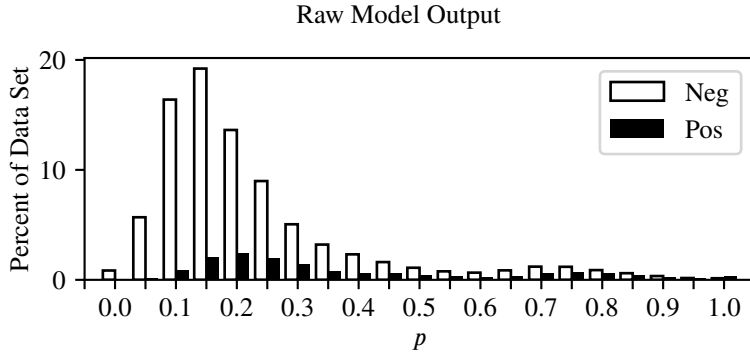


RFC\_5\_Fold\_Hard\_Test\_Transformed\_100



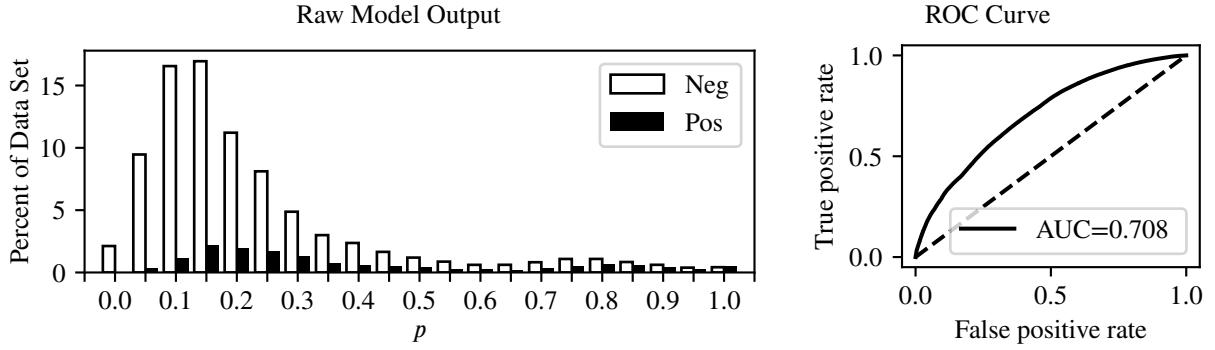
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	1	0	0.00	1	605,609	0	107,956	0.15	1.00	5.61	1.00
0.05	19,650	328	0.02	19,651	585,959	328	107,628	0.16	1.00	5.43	0.97
0.10	107,781	4,744	0.04	127,432	478,178	5,072	102,884	0.18	0.95	4.43	0.81
0.15	162,280	15,837	0.09	289,712	315,898	20,909	87,047	0.22	0.81	2.93	0.56
0.20	115,014	20,184	0.15	404,726	200,884	41,093	66,863	0.25	0.62	1.86	0.38
0.25	69,016	15,326	0.18	473,742	131,868	56,419	51,537	0.28	0.48	1.22	0.26
0.30	34,685	9,256	0.21	508,427	97,183	65,675	42,281	0.30	0.39	0.90	0.20
0.35	23,585	5,614	0.19	532,012	73,598	71,289	36,667	0.33	0.34	0.68	0.15
0.40	14,975	5,081	0.25	546,987	58,623	76,370	31,586	0.35	0.29	0.54	0.13
0.45	9,676	3,257	0.25	556,663	48,947	79,627	28,329	0.37	0.26	0.45	0.11
0.50	6,403	2,553	0.29	563,066	42,544	82,180	25,776	0.38	0.24	0.39	0.10
0.55	5,723	1,928	0.25	568,789	36,821	84,108	23,848	0.39	0.22	0.34	0.09
0.60	8,514	3,591	0.30	577,303	28,307	87,699	20,257	0.42	0.19	0.26	0.07
0.65	10,291	5,753	0.36	587,594	18,016	93,452	14,504	0.45	0.13	0.17	0.05
0.70	8,059	5,367	0.40	595,653	9,957	98,819	9,137	0.48	0.08	0.09	0.03
0.75	5,285	3,884	0.42	600,938	4,672	102,703	5,253	0.53	0.05	0.04	0.01
0.80	2,728	2,140	0.44	603,666	1,944	104,843	3,113	0.62	0.03	0.02	0.01
0.85	1,127	1,345	0.54	604,793	817	106,188	1,768	0.68	0.02	0.01	0.00
0.90	554	994	0.64	605,347	263	107,182	774	0.75	0.01	0.00	0.00
0.95	221	587	0.73	605,568	42	107,769	187	0.82	0.00	0.00	0.00
1.00	42	187	0.82	605,610	0	107,956	0	nan	0.00	0.00	0.00

RFC\_5\_Fold\_Hard\_Test\_Transformed\_98



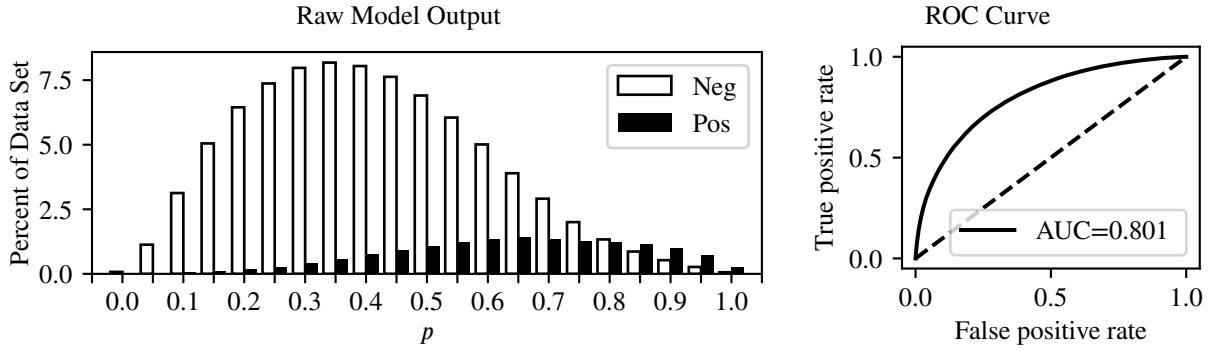
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	6,057	62	0.01	6,057	599,553	62	107,894	0.15	1.00	5.55	0.99
0.05	40,606	1,121	0.03	46,663	558,947	1,183	106,773	0.16	0.99	5.18	0.93
0.10	116,973	6,456	0.05	163,636	441,974	7,639	100,317	0.18	0.93	4.09	0.76
0.15	137,089	14,893	0.10	300,725	304,885	22,532	85,424	0.22	0.79	2.82	0.55
0.20	97,245	17,203	0.15	397,970	207,640	39,735	68,221	0.25	0.63	1.92	0.39
0.25	64,107	13,658	0.18	462,077	143,533	53,393	54,563	0.28	0.51	1.33	0.28
0.30	36,054	9,767	0.21	498,131	107,479	63,160	44,796	0.29	0.41	1.00	0.21
0.35	22,888	5,315	0.19	521,019	84,591	68,475	39,481	0.32	0.37	0.78	0.17
0.40	16,546	4,370	0.21	537,565	68,045	72,845	35,111	0.34	0.33	0.63	0.14
0.45	11,525	4,266	0.27	549,090	56,520	77,111	30,845	0.35	0.29	0.52	0.12
0.50	7,849	2,617	0.25	556,939	48,671	79,728	28,228	0.37	0.26	0.45	0.11
0.55	5,514	2,207	0.29	562,453	43,157	81,935	26,021	0.38	0.24	0.40	0.10
0.60	4,668	1,583	0.25	567,121	38,489	83,518	24,438	0.39	0.23	0.36	0.09
0.65	6,163	2,346	0.28	573,284	32,326	85,864	22,092	0.41	0.20	0.30	0.08
0.70	8,564	4,201	0.33	581,848	23,762	90,065	17,891	0.43	0.17	0.22	0.06
0.75	8,458	5,040	0.37	590,306	15,304	95,105	12,851	0.46	0.12	0.14	0.04
0.80	6,321	4,457	0.41	596,627	8,983	99,562	8,394	0.48	0.08	0.08	0.02
0.85	4,304	3,136	0.42	600,931	4,679	102,698	5,258	0.53	0.05	0.04	0.01
0.90	2,461	1,896	0.44	603,392	2,218	104,594	3,362	0.60	0.03	0.02	0.01
0.95	1,184	1,266	0.52	604,576	1,034	105,860	2,096	0.67	0.02	0.01	0.00
1.00	1,034	2,096	0.67	605,610	0	107,956	0	nan	0.00	0.00	0.00

RFC\_5\_Fold\_Hard\_Test\_Transformed\_95



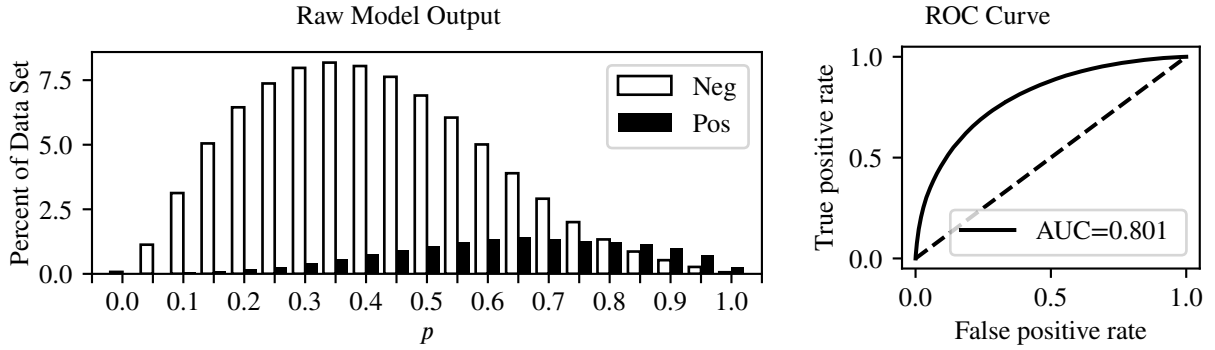
	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
$p$											
0.00	15,142	240	0.02	15,142	590,468	240	107,716	0.15	1.00	5.47	0.98
0.05	67,546	2,407	0.03	82,688	522,922	2,647	105,309	0.17	0.98	4.84	0.88
0.10	118,148	8,082	0.06	200,836	404,774	10,729	97,227	0.19	0.90	3.75	0.70
0.15	120,937	15,507	0.11	321,773	283,837	26,236	81,720	0.22	0.76	2.63	0.51
0.20	80,019	14,275	0.15	401,792	203,818	40,511	67,445	0.25	0.62	1.89	0.38
0.25	57,912	12,362	0.18	459,704	145,906	52,873	55,083	0.27	0.51	1.35	0.28
0.30	34,782	9,249	0.21	494,486	111,124	62,122	45,834	0.29	0.42	1.03	0.22
0.35	21,385	5,163	0.19	515,871	89,739	67,285	40,671	0.31	0.38	0.83	0.18
0.40	16,894	4,201	0.20	532,765	72,845	71,486	36,470	0.33	0.34	0.67	0.15
0.45	11,791	3,808	0.24	544,556	61,054	75,294	32,662	0.35	0.30	0.57	0.13
0.50	8,522	3,136	0.27	553,078	52,532	78,430	29,526	0.36	0.27	0.49	0.11
0.55	6,215	2,195	0.26	559,293	46,317	80,625	27,331	0.37	0.25	0.43	0.10
0.60	4,371	1,744	0.29	563,664	41,946	82,369	25,587	0.38	0.24	0.39	0.09
0.65	4,398	1,473	0.25	568,062	37,548	83,842	24,114	0.39	0.22	0.35	0.09
0.70	5,864	2,317	0.28	573,926	31,684	86,159	21,797	0.41	0.20	0.29	0.07
0.75	7,741	3,797	0.33	581,667	23,943	89,956	18,000	0.43	0.17	0.22	0.06
0.80	7,757	4,590	0.37	589,424	16,186	94,546	13,410	0.45	0.12	0.15	0.04
0.85	5,996	4,103	0.41	595,420	10,190	98,649	9,307	0.48	0.09	0.09	0.03
0.90	4,395	3,176	0.42	599,815	5,795	101,825	6,131	0.51	0.06	0.05	0.02
0.95	2,773	2,175	0.44	602,588	3,022	104,000	3,956	0.57	0.04	0.03	0.01
1.00	3,022	3,956	0.57	605,610	0	107,956	0	nan	0.00	0.00	0.00

BRFC\_5\_Fold\_alpha\_0\_5\_Hard\_Test



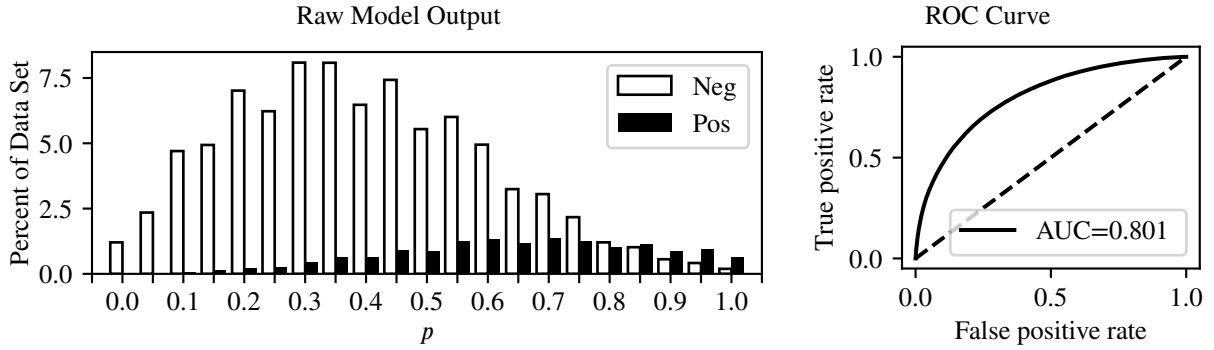
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	539	1	0.00	539	605,071	1	107,955	0.15	1.00	5.60	1.00
0.05	8,059	70	0.01	8,598	597,012	71	107,885	0.15	1.00	5.53	0.99
0.10	22,328	286	0.01	30,926	574,684	357	107,599	0.16	1.00	5.32	0.96
0.15	36,038	633	0.02	66,964	538,646	990	106,966	0.17	0.99	4.99	0.90
0.20	46,017	1,248	0.03	112,981	492,629	2,238	105,718	0.18	0.98	4.56	0.84
0.25	52,604	1,928	0.04	165,585	440,025	4,166	103,790	0.19	0.96	4.08	0.76
0.30	56,905	2,868	0.05	222,490	383,120	7,034	100,922	0.21	0.93	3.55	0.68
0.35	58,370	3,945	0.06	280,860	324,750	10,979	96,977	0.23	0.90	3.01	0.59
0.40	57,422	5,250	0.08	338,282	267,328	16,229	91,727	0.26	0.85	2.48	0.50
0.45	54,438	6,402	0.11	392,720	212,890	22,631	85,325	0.29	0.79	1.97	0.42
0.50	49,277	7,561	0.13	441,997	163,613	30,192	77,764	0.32	0.72	1.52	0.34
0.55	43,177	8,771	0.17	485,174	120,436	38,963	68,993	0.36	0.64	1.12	0.27
0.60	35,756	9,573	0.21	520,930	84,680	48,536	59,420	0.41	0.55	0.78	0.20
0.65	27,800	10,028	0.27	548,730	56,880	58,564	49,392	0.46	0.46	0.53	0.15
0.70	20,763	9,639	0.32	569,493	36,117	68,203	39,753	0.52	0.37	0.33	0.11
0.75	14,298	8,927	0.38	583,791	21,819	77,130	30,826	0.59	0.29	0.20	0.07
0.80	9,513	8,678	0.48	593,304	12,306	85,808	22,148	0.64	0.21	0.11	0.05
0.85	6,169	8,063	0.57	599,473	6,137	93,871	14,085	0.70	0.13	0.06	0.03
0.90	3,780	7,181	0.66	603,253	2,357	101,052	6,904	0.75	0.06	0.02	0.01
0.95	1,911	5,155	0.73	605,164	446	106,207	1,749	0.80	0.02	0.00	0.00
1.00	446	1,749	0.80	605,610	0	107,956	0	nan	0.00	0.00	0.00

BRFC\_5\_Fold\_alpha\_0\_5\_Hard\_Test\_Transformed\_100



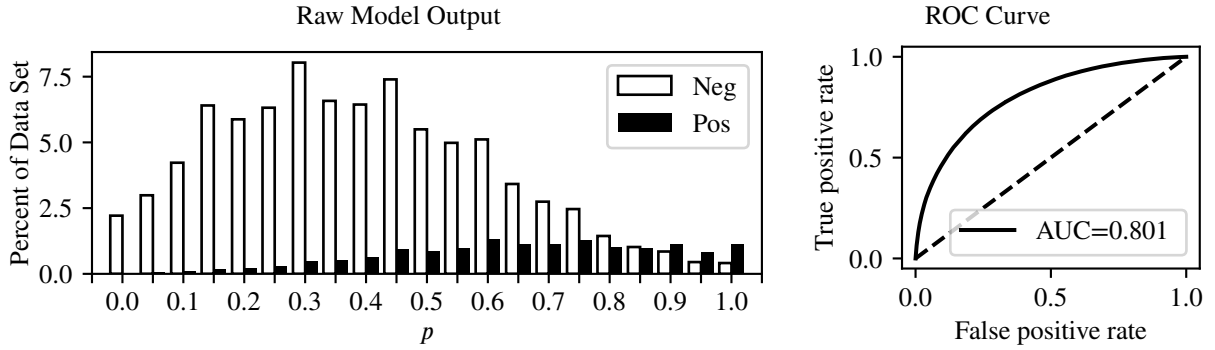
	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
p											
0.00	539	1	0.00	539	605,071	1	107,955	0.15	1.00	5.60	1.00
0.05	8,059	70	0.01	8,598	597,012	71	107,885	0.15	1.00	5.53	0.99
0.10	22,328	286	0.01	30,926	574,684	357	107,599	0.16	1.00	5.32	0.96
0.15	36,038	633	0.02	66,964	538,646	990	106,966	0.17	0.99	4.99	0.90
0.20	46,017	1,248	0.03	112,981	492,629	2,238	105,718	0.18	0.98	4.56	0.84
0.25	52,604	1,928	0.04	165,585	440,025	4,166	103,790	0.19	0.96	4.08	0.76
0.30	56,905	2,868	0.05	222,490	383,120	7,034	100,922	0.21	0.93	3.55	0.68
0.35	58,370	3,945	0.06	280,860	324,750	10,979	96,977	0.23	0.90	3.01	0.59
0.40	57,422	5,250	0.08	338,282	267,328	16,229	91,727	0.26	0.85	2.48	0.50
0.45	54,438	6,402	0.11	392,720	212,890	22,631	85,325	0.29	0.79	1.97	0.42
0.50	49,277	7,561	0.13	441,997	163,613	30,192	77,764	0.32	0.72	1.52	0.34
0.55	43,177	8,771	0.17	485,174	120,436	38,963	68,993	0.36	0.64	1.12	0.27
0.60	35,756	9,573	0.21	520,930	84,680	48,536	59,420	0.41	0.55	0.78	0.20
0.65	27,800	10,028	0.27	548,730	56,880	58,564	49,392	0.46	0.46	0.53	0.15
0.70	20,763	9,639	0.32	569,493	36,117	68,203	39,753	0.52	0.37	0.33	0.11
0.75	14,298	8,927	0.38	583,791	21,819	77,130	30,826	0.59	0.29	0.20	0.07
0.80	9,513	8,678	0.48	593,304	12,306	85,808	22,148	0.64	0.21	0.11	0.05
0.85	6,169	8,063	0.57	599,473	6,137	93,871	14,085	0.70	0.13	0.06	0.03
0.90	3,780	7,181	0.66	603,253	2,357	101,052	6,904	0.75	0.06	0.02	0.01
0.95	1,911	5,155	0.73	605,164	446	106,207	1,749	0.80	0.02	0.00	0.00
1.00	446	1,749	0.80	605,610	0	107,956	0	nan	0.00	0.00	0.00

BRFC\_5\_Fold\_alpha\_0\_5\_Hard\_Test\_Transformed\_98



$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	8,598	71	0.01	8,598	597,012	71	107,885	0.15	1.00	5.53	0.99
0.05	16,754	213	0.01	25,352	580,258	284	107,672	0.16	1.00	5.37	0.96
0.10	33,555	535	0.02	58,907	546,703	819	107,137	0.16	0.99	5.06	0.92
0.15	35,219	860	0.02	94,126	511,484	1,679	106,277	0.17	0.98	4.74	0.87
0.20	50,071	1,618	0.03	144,197	461,413	3,297	104,659	0.18	0.97	4.27	0.79
0.25	44,431	1,909	0.04	188,628	416,982	5,206	102,750	0.20	0.95	3.86	0.73
0.30	57,727	3,275	0.05	246,355	359,255	8,481	99,475	0.22	0.92	3.33	0.64
0.35	57,683	4,502	0.07	304,038	301,572	12,983	94,973	0.24	0.88	2.79	0.56
0.40	46,193	4,513	0.09	350,231	255,379	17,496	90,460	0.26	0.84	2.37	0.48
0.45	53,003	6,554	0.11	403,234	202,376	24,050	83,906	0.29	0.78	1.87	0.40
0.50	39,556	6,264	0.14	442,790	162,820	30,314	77,642	0.32	0.72	1.51	0.34
0.55	42,878	8,766	0.17	485,668	119,942	39,080	68,876	0.36	0.64	1.11	0.26
0.60	35,301	9,459	0.21	520,969	84,641	48,539	59,417	0.41	0.55	0.78	0.20
0.65	23,147	8,234	0.26	544,116	61,494	56,773	51,183	0.45	0.47	0.57	0.16
0.70	21,793	9,627	0.31	565,909	39,701	66,400	41,556	0.51	0.38	0.37	0.11
0.75	15,492	8,940	0.37	581,401	24,209	75,340	32,616	0.57	0.30	0.22	0.08
0.80	8,607	7,188	0.46	590,008	15,602	82,528	25,428	0.62	0.24	0.14	0.06
0.85	7,280	8,166	0.53	597,288	8,322	90,694	17,262	0.67	0.16	0.08	0.04
0.90	3,988	6,272	0.61	601,276	4,334	96,966	10,990	0.72	0.10	0.04	0.02
0.95	2,965	6,568	0.69	604,241	1,369	103,534	4,422	0.76	0.04	0.01	0.01
1.00	1,369	4,422	0.76	605,610	0	107,956	0	nan	0.00	0.00	0.00

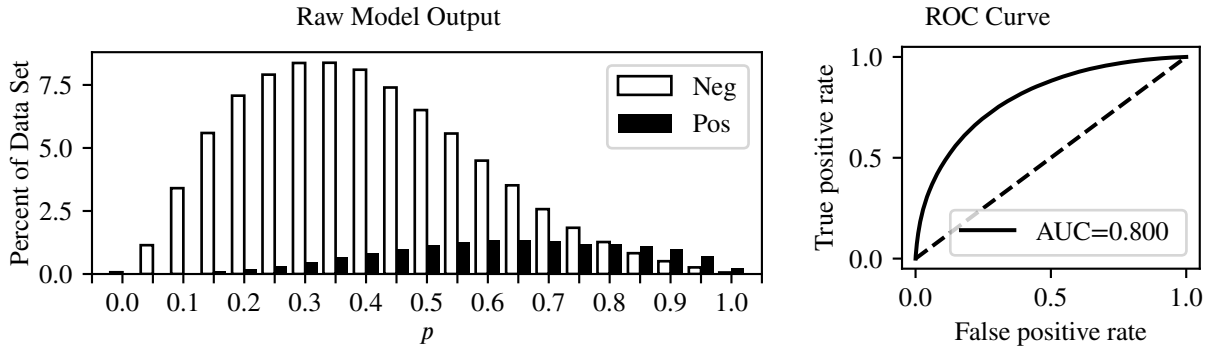
BRFC\_5\_Fold\_alpha\_0\_5\_Hard\_Test\_Transformed\_95



$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	15,796	157	0.01	15,796	589,814	157	107,799	0.15	1.00	5.46	0.98
0.05	21,323	285	0.01	37,119	568,491	442	107,514	0.16	1.00	5.27	0.95
0.10	30,162	555	0.02	67,281	538,329	997	106,959	0.17	0.99	4.99	0.90
0.15	45,700	1,241	0.03	112,981	492,629	2,238	105,718	0.18	0.98	4.56	0.84
0.20	41,939	1,503	0.03	154,920	450,690	3,741	104,215	0.19	0.97	4.17	0.78
0.25	45,091	2,042	0.04	200,011	405,599	5,783	102,173	0.20	0.95	3.76	0.71
0.30	57,336	3,472	0.06	257,347	348,263	9,255	98,701	0.22	0.91	3.23	0.63
0.35	46,948	3,745	0.07	304,295	301,315	13,000	94,956	0.24	0.88	2.79	0.56
0.40	45,953	4,497	0.09	350,248	255,362	17,497	90,459	0.26	0.84	2.37	0.48
0.45	52,775	6,521	0.11	403,023	202,587	24,018	83,938	0.29	0.78	1.88	0.40
0.50	39,220	6,221	0.14	442,243	163,367	30,239	77,717	0.32	0.72	1.51	0.34
0.55	35,557	7,011	0.16	477,800	127,810	37,250	70,706	0.36	0.65	1.18	0.28
0.60	36,486	9,406	0.20	514,286	91,324	46,656	61,300	0.40	0.57	0.85	0.21
0.65	24,392	8,010	0.25	538,678	66,932	54,666	53,290	0.44	0.49	0.62	0.17
0.70	19,590	7,993	0.29	558,268	47,342	62,659	45,297	0.49	0.42	0.44	0.13
0.75	17,582	9,178	0.34	575,850	29,760	71,837	36,119	0.55	0.33	0.28	0.09
0.80	10,280	7,207	0.41	586,130	19,480	79,044	28,912	0.60	0.27	0.18	0.07
0.85	7,284	6,910	0.49	593,414	12,196	85,954	22,002	0.64	0.20	0.11	0.05
0.90	6,064	7,930	0.57	599,478	6,132	93,884	14,072	0.70	0.13	0.06	0.03
0.95	3,198	5,951	0.65	602,676	2,934	99,835	8,121	0.73	0.08	0.03	0.02
1.00	2,934	8,121	0.73	605,610	0	107,956	0	nan	0.00	0.00	0.00

**16.2. Balanced Random Forest Classifier,  $\alpha$  balanced**

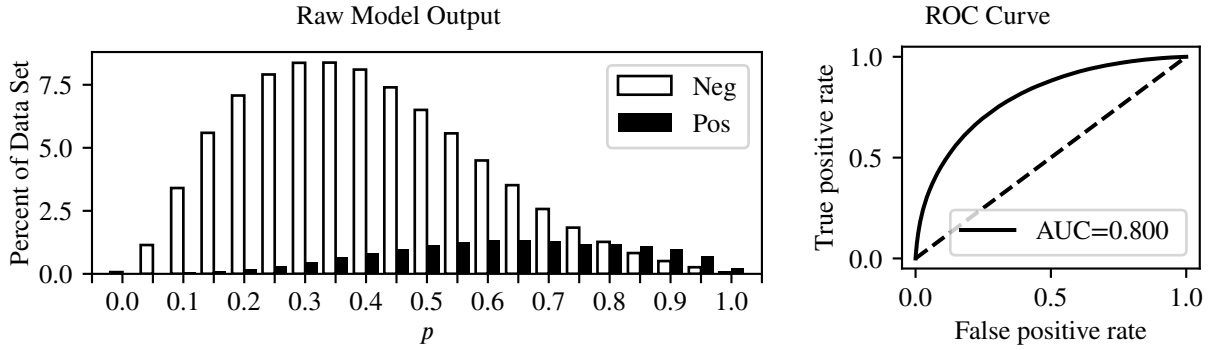
BRFC\_5\_Fold\_alpha\_balanced\_Hard\_Test



$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	494	1	0.00	494	605,116	1	107,955	0.15	1.00	5.61	1.00
0.05	8,161	66	0.01	8,655	596,955	67	107,889	0.15	1.00	5.53	0.99
0.10	24,296	287	0.01	32,951	572,659	354	107,602	0.16	1.00	5.30	0.95
0.15	39,914	694	0.02	72,865	532,745	1,048	106,908	0.17	0.99	4.93	0.90
0.20	50,482	1,388	0.03	123,347	482,263	2,436	105,520	0.18	0.98	4.47	0.82
0.25	56,431	2,197	0.04	179,778	425,832	4,633	103,323	0.20	0.96	3.94	0.74
0.30	59,731	3,263	0.05	239,509	366,101	7,896	100,060	0.21	0.93	3.39	0.65
0.35	59,796	4,615	0.07	299,305	306,305	12,511	95,445	0.24	0.88	2.84	0.56
0.40	57,825	5,689	0.09	357,130	248,480	18,200	89,756	0.27	0.83	2.30	0.47
0.45	52,789	6,967	0.12	409,919	195,691	25,167	82,789	0.30	0.77	1.81	0.39
0.50	46,405	7,967	0.15	456,324	149,286	33,134	74,822	0.33	0.69	1.38	0.31
0.55	39,767	8,860	0.18	496,091	109,519	41,994	65,962	0.38	0.61	1.01	0.25
0.60	32,094	9,438	0.23	528,185	77,425	51,432	56,524	0.42	0.52	0.72	0.19
0.65	25,106	9,370	0.27	553,291	52,319	60,802	47,154	0.47	0.44	0.48	0.14
0.70	18,361	9,076	0.33	571,652	33,958	69,878	38,078	0.53	0.35	0.31	0.10
0.75	13,086	8,483	0.39	584,738	20,872	78,361	29,595	0.59	0.27	0.19	0.07
0.80	9,052	8,301	0.48	593,790	11,820	86,662	21,294	0.64	0.20	0.11	0.05
0.85	5,890	7,756	0.57	599,680	5,930	94,418	13,538	0.70	0.13	0.05	0.03
0.90	3,623	6,836	0.65	603,303	2,307	101,254	6,702	0.74	0.06	0.02	0.01
0.95	1,876	5,020	0.73	605,179	431	106,274	1,682	0.80	0.02	0.00	0.00
1.00	431	1,682	0.80	605,610	0	107,956	0	nan	0.00	0.00	0.00

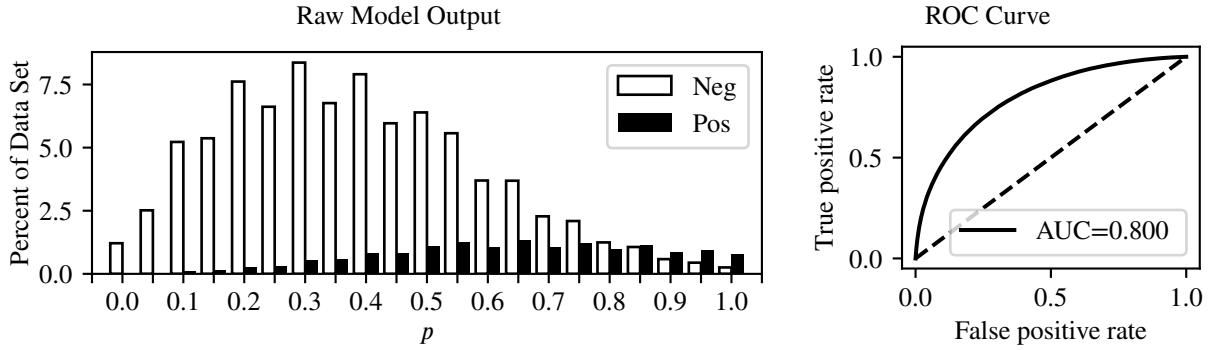


BRFC\_5\_Fold\_alpha\_balanced\_Hard\_Test\_Transformed\_100



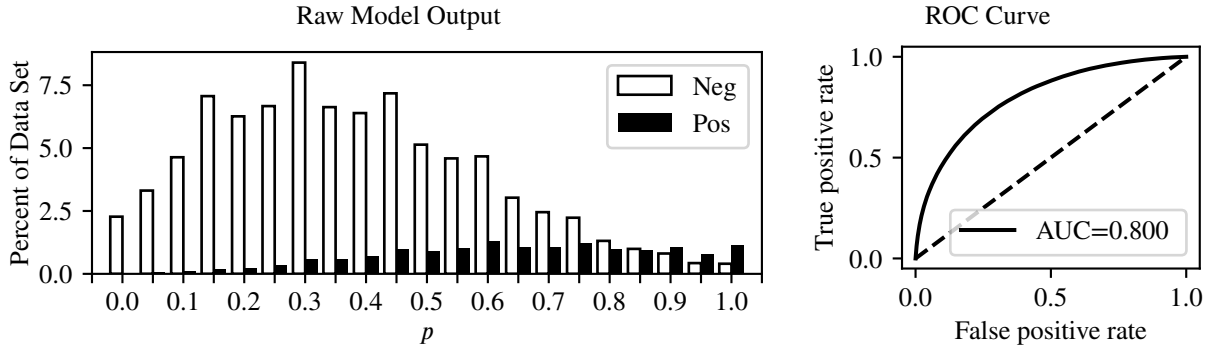
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	494	1	0.00	494	605,116	1	107,955	0.15	1.00	5.61	1.00
0.05	8,161	66	0.01	8,655	596,955	67	107,889	0.15	1.00	5.53	0.99
0.10	24,296	287	0.01	32,951	572,659	354	107,602	0.16	1.00	5.30	0.95
0.15	39,914	694	0.02	72,865	532,745	1,048	106,908	0.17	0.99	4.93	0.90
0.20	50,482	1,388	0.03	123,347	482,263	2,436	105,520	0.18	0.98	4.47	0.82
0.25	56,431	2,197	0.04	179,778	425,832	4,633	103,323	0.20	0.96	3.94	0.74
0.30	59,731	3,263	0.05	239,509	366,101	7,896	100,060	0.21	0.93	3.39	0.65
0.35	59,796	4,615	0.07	299,305	306,305	12,511	95,445	0.24	0.88	2.84	0.56
0.40	57,825	5,689	0.09	357,130	248,480	18,200	89,756	0.27	0.83	2.30	0.47
0.45	52,789	6,967	0.12	409,919	195,691	25,167	82,789	0.30	0.77	1.81	0.39
0.50	46,405	7,967	0.15	456,324	149,286	33,134	74,822	0.33	0.69	1.38	0.31
0.55	39,767	8,860	0.18	496,091	109,519	41,994	65,962	0.38	0.61	1.01	0.25
0.60	32,094	9,438	0.23	528,185	77,425	51,432	56,524	0.42	0.52	0.72	0.19
0.65	25,106	9,370	0.27	553,291	52,319	60,802	47,154	0.47	0.44	0.48	0.14
0.70	18,361	9,076	0.33	571,652	33,958	69,878	38,078	0.53	0.35	0.31	0.10
0.75	13,086	8,483	0.39	584,738	20,872	78,361	29,595	0.59	0.27	0.19	0.07
0.80	9,052	8,301	0.48	593,790	11,820	86,662	21,294	0.64	0.20	0.11	0.05
0.85	5,890	7,756	0.57	599,680	5,930	94,418	13,538	0.70	0.13	0.05	0.03
0.90	3,623	6,836	0.65	603,303	2,307	101,254	6,702	0.74	0.06	0.02	0.01
0.95	1,876	5,020	0.73	605,179	431	106,274	1,682	0.80	0.02	0.00	0.00
1.00	431	1,682	0.80	605,610	0	107,956	0	nan	0.00	0.00	0.00

BRFC\_5\_Fold\_alpha\_balanced\_Hard\_Test\_Transformed\_98



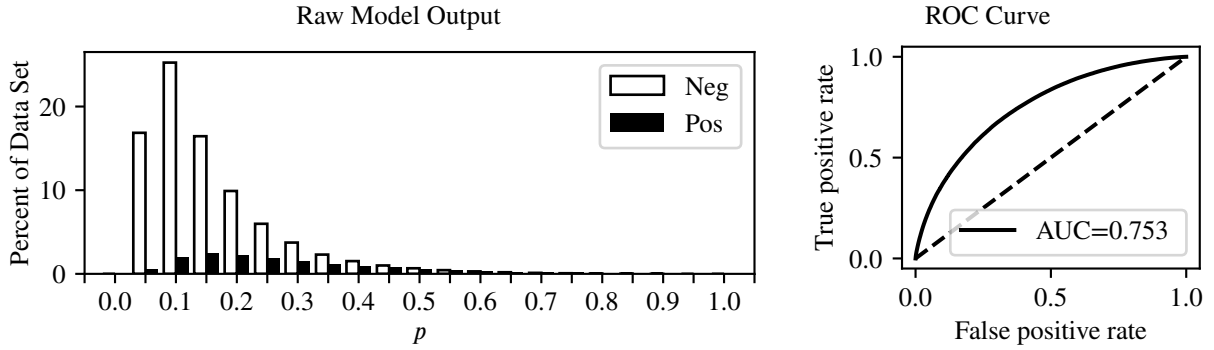
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	8,655	67	0.01	8,655	596,955	67	107,889	0.15	1.00	5.53	0.99
0.05	17,959	206	0.01	26,614	578,996	273	107,683	0.16	1.00	5.36	0.96
0.10	37,283	600	0.02	63,897	541,713	873	107,083	0.17	0.99	5.02	0.91
0.15	38,320	937	0.02	102,217	503,393	1,810	106,146	0.17	0.98	4.66	0.85
0.20	54,345	1,850	0.03	156,562	449,048	3,660	104,296	0.19	0.97	4.16	0.78
0.25	47,227	2,150	0.04	203,789	401,821	5,810	102,146	0.20	0.95	3.72	0.71
0.30	59,707	3,802	0.06	263,496	342,114	9,612	98,344	0.22	0.91	3.17	0.62
0.35	48,258	3,982	0.08	311,754	293,856	13,594	94,362	0.24	0.87	2.72	0.54
0.40	56,415	5,929	0.10	368,169	237,441	19,523	88,433	0.27	0.82	2.20	0.46
0.45	42,555	5,732	0.12	410,724	194,886	25,255	82,701	0.30	0.77	1.81	0.39
0.50	45,624	7,882	0.15	456,348	149,262	33,137	74,819	0.33	0.69	1.38	0.31
0.55	39,744	8,858	0.18	496,092	109,518	41,995	65,961	0.38	0.61	1.01	0.25
0.60	26,383	7,534	0.22	522,475	83,135	49,529	58,427	0.41	0.54	0.77	0.20
0.65	26,322	9,421	0.26	548,797	56,813	58,950	49,006	0.46	0.45	0.53	0.15
0.70	16,258	7,375	0.31	565,055	40,555	66,325	41,631	0.51	0.39	0.38	0.12
0.75	14,933	8,586	0.37	579,988	25,622	74,911	33,045	0.56	0.31	0.24	0.08
0.80	8,887	6,830	0.43	588,875	16,735	81,741	26,215	0.61	0.24	0.16	0.06
0.85	7,592	8,080	0.52	596,467	9,143	89,821	18,135	0.66	0.17	0.08	0.04
0.90	4,162	6,157	0.60	600,629	4,981	95,978	11,978	0.71	0.11	0.05	0.02
0.95	3,163	6,534	0.67	603,792	1,818	102,512	5,444	0.75	0.05	0.02	0.01
1.00	1,818	5,444	0.75	605,610	0	107,956	0	nan	0.00	0.00	0.00

BRFC\_5\_Fold\_alpha\_balanced\_Hard\_Test\_Transformed\_95



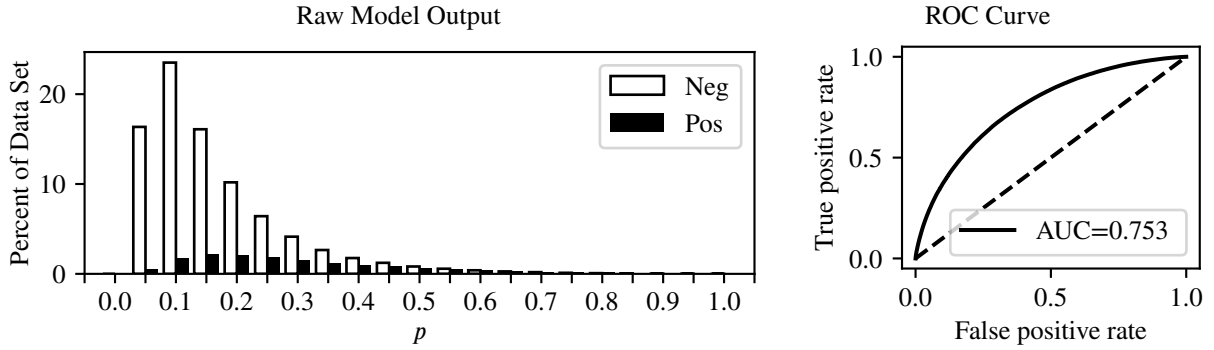
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	16,222	152	0.01	16,222	589,388	152	107,804	0.15	1.00	5.46	0.98
0.05	23,625	301	0.01	39,847	565,763	453	107,503	0.16	1.00	5.24	0.94
0.10	33,078	595	0.02	72,925	532,685	1,048	106,908	0.17	0.99	4.93	0.90
0.15	50,422	1,388	0.03	123,347	482,263	2,436	105,520	0.18	0.98	4.47	0.82
0.20	44,687	1,681	0.04	168,034	437,576	4,117	103,839	0.19	0.96	4.05	0.76
0.25	47,594	2,327	0.05	215,628	389,982	6,444	101,512	0.21	0.94	3.61	0.69
0.30	59,935	4,062	0.06	275,563	330,047	10,506	97,450	0.23	0.90	3.06	0.60
0.35	47,300	4,160	0.08	322,863	282,747	14,666	93,290	0.25	0.86	2.62	0.53
0.40	45,613	4,889	0.10	368,476	237,134	19,555	88,401	0.27	0.82	2.20	0.46
0.45	51,215	7,078	0.12	419,691	185,919	26,633	81,323	0.30	0.75	1.72	0.37
0.50	36,657	6,504	0.15	456,348	149,262	33,137	74,819	0.33	0.69	1.38	0.31
0.55	32,756	7,181	0.18	489,104	116,506	40,318	67,638	0.37	0.63	1.08	0.26
0.60	33,332	9,199	0.22	522,436	83,174	49,517	58,439	0.41	0.54	0.77	0.20
0.65	21,609	7,558	0.26	544,045	61,565	57,075	50,881	0.45	0.47	0.57	0.16
0.70	17,502	7,553	0.30	561,547	44,063	64,628	43,328	0.50	0.40	0.41	0.12
0.75	15,927	8,593	0.35	577,474	28,136	73,221	34,735	0.55	0.32	0.26	0.09
0.80	9,357	6,850	0.42	586,831	18,779	80,071	27,885	0.60	0.26	0.17	0.07
0.85	7,083	6,723	0.49	593,914	11,696	86,794	21,162	0.64	0.20	0.11	0.05
0.90	5,772	7,629	0.57	599,686	5,924	94,423	13,533	0.70	0.13	0.05	0.03
0.95	3,053	5,586	0.65	602,739	2,871	100,009	7,947	0.73	0.07	0.03	0.02
1.00	2,871	7,947	0.73	605,610	0	107,956	0	nan	0.00	0.00	0.00

LogReg\_5\_Fold\_alpha\_0\_5\_Hard\_Test



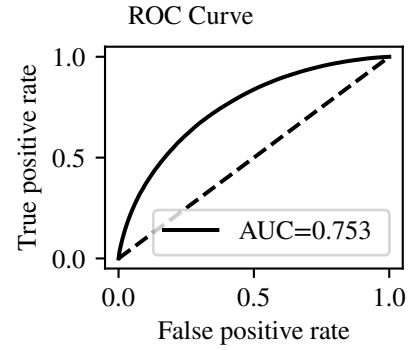
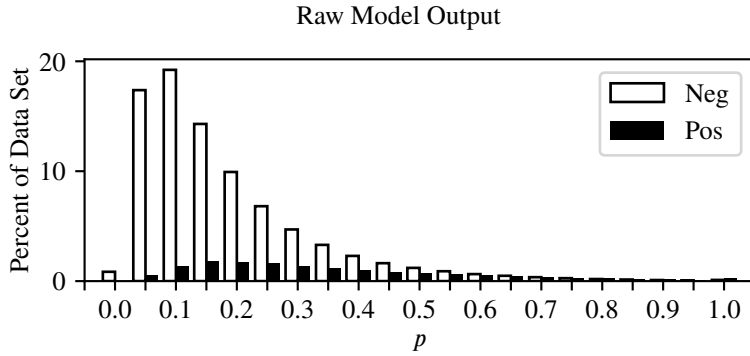
	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
p											
0.00	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.05	120,294	3,462	0.03	120,294	485,316	3,462	104,494	0.18	0.97	4.50	0.83
0.10	180,183	13,786	0.07	300,477	305,133	17,248	90,708	0.23	0.84	2.83	0.55
0.15	117,385	17,103	0.13	417,862	187,748	34,351	73,605	0.28	0.68	1.74	0.37
0.20	70,681	15,755	0.18	488,543	117,067	50,106	57,850	0.33	0.54	1.08	0.25
0.25	42,697	12,863	0.23	531,240	74,370	62,969	44,987	0.38	0.42	0.69	0.17
0.30	26,686	10,398	0.28	557,926	47,684	73,367	34,589	0.42	0.32	0.44	0.12
0.35	16,433	8,285	0.34	574,359	31,251	81,652	26,304	0.46	0.24	0.29	0.08
0.40	10,872	6,676	0.38	585,231	20,379	88,328	19,628	0.49	0.18	0.19	0.06
0.45	7,151	5,335	0.43	592,382	13,228	93,663	14,293	0.52	0.13	0.12	0.04
0.50	4,753	4,056	0.46	597,135	8,475	97,719	10,237	0.55	0.09	0.08	0.03
0.55	3,155	3,108	0.50	600,290	5,320	100,827	7,129	0.57	0.07	0.05	0.02
0.60	2,112	2,267	0.52	602,402	3,208	103,094	4,862	0.60	0.05	0.03	0.01
0.65	1,366	1,635	0.54	603,768	1,842	104,729	3,227	0.64	0.03	0.02	0.01
0.70	844	1,172	0.58	604,612	998	105,901	2,055	0.67	0.02	0.01	0.00
0.75	516	898	0.64	605,128	482	106,799	1,157	0.71	0.01	0.00	0.00
0.80	305	688	0.69	605,433	177	107,487	469	0.73	0.00	0.00	0.00
0.85	153	356	0.70	605,586	24	107,843	113	0.82	0.00	0.00	0.00
0.90	22	107	0.83	605,608	2	107,950	6	0.75	0.00	0.00	0.00
0.95	2	6	0.75	605,610	0	107,956	0	nan	0.00	0.00	0.00
1.00	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00

LogReg\_5\_Fold\_alpha\_0\_5\_Hard\_Test\_Transformed\_100



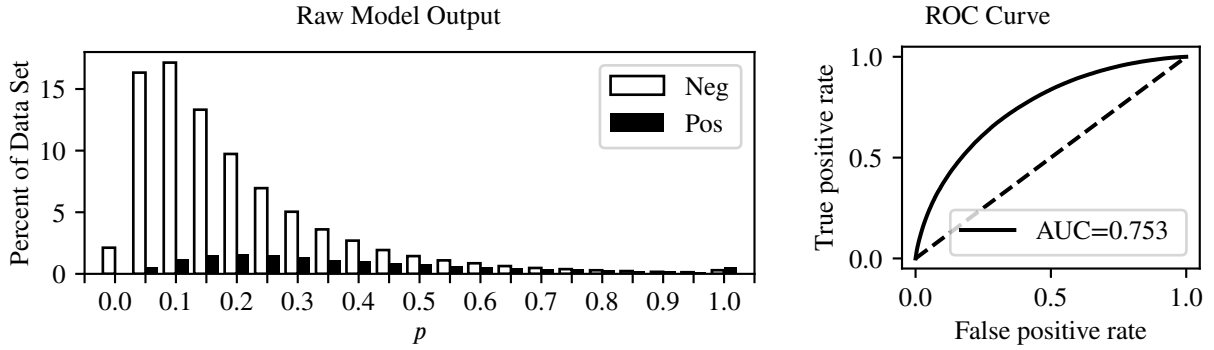
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	1	0	0.00	1	605,609	0	107,956	0.15	1.00	5.61	1.00
0.05	116,707	3,321	0.03	116,708	488,902	3,321	104,635	0.18	0.97	4.53	0.83
0.10	167,772	12,165	0.07	284,480	321,130	15,486	92,470	0.22	0.86	2.97	0.58
0.15	114,824	15,592	0.12	399,304	206,306	31,078	76,878	0.27	0.71	1.91	0.40
0.20	72,677	14,703	0.17	471,981	133,629	45,781	62,175	0.32	0.58	1.24	0.27
0.25	45,809	12,779	0.22	517,790	87,820	58,560	49,396	0.36	0.46	0.81	0.19
0.30	29,518	10,463	0.26	547,308	58,302	69,023	38,933	0.40	0.36	0.54	0.14
0.35	18,930	8,331	0.31	566,238	39,372	77,354	30,602	0.44	0.28	0.36	0.10
0.40	12,556	6,865	0.35	578,794	26,816	84,219	23,737	0.47	0.22	0.25	0.07
0.45	8,766	5,755	0.40	587,560	18,050	89,974	17,982	0.50	0.17	0.17	0.05
0.50	5,844	4,533	0.44	593,404	12,206	94,507	13,449	0.52	0.12	0.11	0.04
0.55	4,077	3,566	0.47	597,481	8,129	98,073	9,883	0.55	0.09	0.08	0.03
0.60	2,829	2,781	0.50	600,310	5,300	100,854	7,102	0.57	0.07	0.05	0.02
0.65	1,941	2,080	0.52	602,251	3,359	102,934	5,022	0.60	0.05	0.03	0.01
0.70	1,350	1,546	0.53	603,601	2,009	104,480	3,476	0.63	0.03	0.02	0.01
0.75	824	1,131	0.58	604,425	1,185	105,611	2,345	0.66	0.02	0.01	0.00
0.80	550	894	0.62	604,975	635	106,505	1,451	0.70	0.01	0.01	0.00
0.85	353	722	0.67	605,328	282	107,227	729	0.72	0.01	0.00	0.00
0.90	200	458	0.70	605,528	82	107,685	271	0.77	0.00	0.00	0.00
0.95	74	233	0.76	605,602	8	107,918	38	0.83	0.00	0.00	0.00
1.00	8	38	0.83	605,610	0	107,956	0	nan	0.00	0.00	0.00

LogReg\_5\_Fold\_alpha\_0\_5\_Hard\_Test\_Transformed\_98



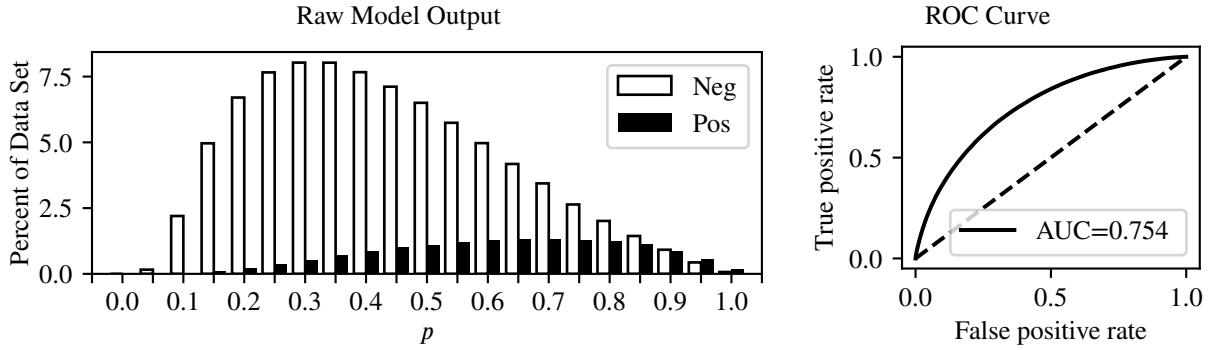
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	6,057	60	0.01	6,057	599,553	60	107,896	0.15	1.00	5.55	0.99
0.05	123,991	3,858	0.03	130,048	475,562	3,918	104,038	0.18	0.96	4.41	0.81
0.10	137,153	9,847	0.07	267,201	338,409	13,765	94,191	0.22	0.87	3.13	0.61
0.15	102,038	12,556	0.11	369,239	236,371	26,321	81,635	0.26	0.76	2.19	0.45
0.20	70,851	12,439	0.15	440,090	165,520	38,760	69,196	0.29	0.64	1.53	0.33
0.25	48,634	11,402	0.19	488,724	116,886	50,162	57,794	0.33	0.54	1.08	0.24
0.30	33,541	9,801	0.23	522,265	83,345	59,963	47,993	0.37	0.44	0.77	0.18
0.35	23,523	8,386	0.26	545,788	59,822	68,349	39,607	0.40	0.37	0.55	0.14
0.40	16,366	7,024	0.30	562,154	43,456	75,373	32,583	0.43	0.30	0.40	0.11
0.45	11,641	5,990	0.34	573,795	31,815	81,363	26,593	0.46	0.25	0.29	0.08
0.50	8,587	5,074	0.37	582,382	23,228	86,437	21,519	0.48	0.20	0.22	0.06
0.55	6,412	4,392	0.41	588,794	16,816	90,829	17,127	0.50	0.16	0.16	0.05
0.60	4,547	3,636	0.44	593,341	12,269	94,465	13,491	0.52	0.12	0.11	0.04
0.65	3,459	2,941	0.46	596,800	8,810	97,406	10,550	0.54	0.10	0.08	0.03
0.70	2,545	2,449	0.49	599,345	6,265	99,855	8,101	0.56	0.08	0.06	0.02
0.75	1,907	1,992	0.51	601,252	4,358	101,847	6,109	0.58	0.06	0.04	0.01
0.80	1,354	1,502	0.53	602,606	3,004	103,349	4,607	0.61	0.04	0.03	0.01
0.85	1,030	1,198	0.54	603,636	1,974	104,547	3,409	0.63	0.03	0.02	0.01
0.90	701	916	0.57	604,337	1,273	105,463	2,493	0.66	0.02	0.01	0.01
0.95	491	766	0.61	604,828	782	106,229	1,727	0.69	0.02	0.01	0.00
1.00	782	1,727	0.69	605,610	0	107,956	0	nan	0.00	0.00	0.00

LogReg\_5\_Fold\_alpha\_0\_5\_Hard\_Test\_Transformed\_95



	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
$p$											
0.00	15,141	184	0.01	15,141	590,469	184	107,772	0.15	1.00	5.47	0.98
0.05	116,529	3,803	0.03	131,670	473,940	3,987	103,969	0.18	0.96	4.39	0.81
0.10	122,329	8,487	0.06	253,999	351,611	12,474	95,482	0.21	0.88	3.26	0.63
0.15	95,056	10,935	0.10	349,055	256,555	23,409	84,547	0.25	0.78	2.38	0.48
0.20	69,426	11,050	0.14	418,481	187,129	34,459	73,497	0.28	0.68	1.73	0.37
0.25	49,630	10,462	0.17	468,111	137,499	44,921	63,035	0.31	0.58	1.27	0.28
0.30	35,963	9,488	0.21	504,074	101,536	54,409	53,547	0.35	0.50	0.94	0.22
0.35	25,749	8,075	0.24	529,823	75,787	62,484	45,472	0.37	0.42	0.70	0.17
0.40	19,236	7,225	0.27	549,059	56,551	69,709	38,247	0.40	0.35	0.52	0.13
0.45	13,786	6,010	0.30	562,845	42,765	75,719	32,237	0.43	0.30	0.40	0.11
0.50	10,281	5,247	0.34	573,126	32,484	80,966	26,990	0.45	0.25	0.30	0.08
0.55	7,812	4,596	0.37	580,938	24,672	85,562	22,394	0.48	0.21	0.23	0.07
0.60	6,129	4,001	0.39	587,067	18,543	89,563	18,393	0.50	0.17	0.17	0.05
0.65	4,508	3,423	0.43	591,575	14,035	92,986	14,970	0.52	0.14	0.13	0.04
0.70	3,406	2,893	0.46	594,981	10,629	95,879	12,077	0.53	0.11	0.10	0.03
0.75	2,727	2,398	0.47	597,708	7,902	98,277	9,679	0.55	0.09	0.07	0.02
0.80	2,079	2,008	0.49	599,787	5,823	100,285	7,671	0.57	0.07	0.05	0.02
0.85	1,605	1,684	0.51	601,392	4,218	101,969	5,987	0.59	0.06	0.04	0.01
0.90	1,174	1,350	0.53	602,566	3,044	103,319	4,637	0.60	0.04	0.03	0.01
0.95	945	1,044	0.52	603,511	2,099	104,363	3,593	0.63	0.03	0.02	0.01
1.00	2,099	3,593	0.63	605,610	0	107,956	0	nan	0.00	0.00	0.00

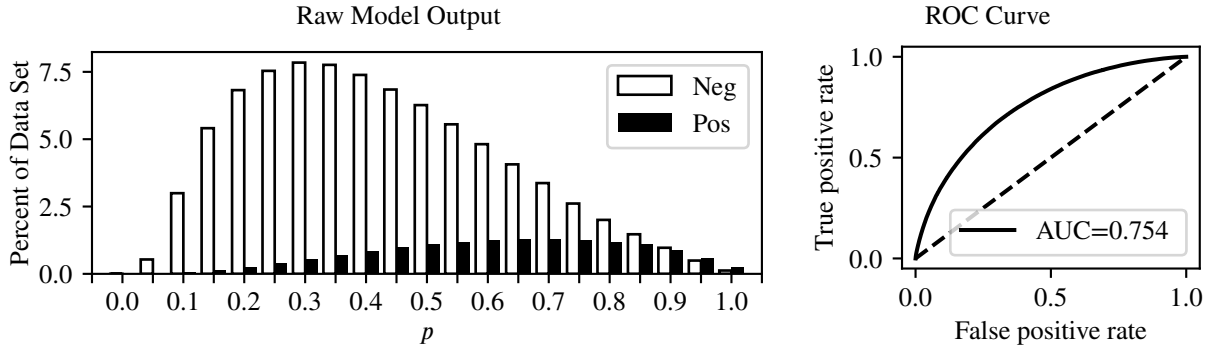
LogReg\_5\_Fold\_alpha\_balanced\_Hard\_Test



$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.05	1,139	13	0.01	1,139	604,471	13	107,943	0.15	1.00	5.60	1.00
0.10	15,694	202	0.01	16,833	588,777	215	107,741	0.15	1.00	5.45	0.98
0.15	35,415	727	0.02	52,248	553,362	942	107,014	0.16	0.99	5.13	0.93
0.20	47,832	1,582	0.03	100,080	505,530	2,524	105,432	0.17	0.98	4.68	0.86
0.25	54,650	2,592	0.05	154,730	450,880	5,116	102,840	0.19	0.95	4.18	0.78
0.30	57,311	3,652	0.06	212,041	393,569	8,768	99,188	0.20	0.92	3.65	0.69
0.35	57,292	4,924	0.08	269,333	336,277	13,692	94,264	0.22	0.87	3.11	0.60
0.40	54,713	6,068	0.10	324,046	281,564	19,760	88,196	0.24	0.82	2.61	0.52
0.45	50,776	7,075	0.12	374,822	230,788	26,835	81,121	0.26	0.75	2.14	0.44
0.50	46,399	7,855	0.14	421,221	184,389	34,690	73,266	0.28	0.68	1.71	0.36
0.55	40,984	8,679	0.17	462,205	143,405	43,369	64,587	0.31	0.60	1.33	0.29
0.60	35,466	9,184	0.21	497,671	107,939	52,553	55,403	0.34	0.51	1.00	0.23
0.65	29,807	9,294	0.24	527,478	78,132	61,847	46,109	0.37	0.43	0.72	0.17
0.70	24,538	9,289	0.27	552,016	53,594	71,136	36,820	0.41	0.34	0.50	0.13
0.75	18,820	9,044	0.32	570,836	34,774	80,180	27,776	0.44	0.26	0.32	0.09
0.80	14,356	8,735	0.38	585,192	20,418	88,915	19,041	0.48	0.18	0.19	0.06
0.85	10,270	7,887	0.43	595,462	10,148	96,802	11,154	0.52	0.10	0.09	0.03
0.90	6,542	6,158	0.48	602,004	3,606	102,960	4,996	0.58	0.05	0.03	0.01
0.95	3,100	3,889	0.56	605,104	506	106,849	1,107	0.69	0.01	0.00	0.00
1.00	506	1,107	0.69	605,610	0	107,956	0	nan	0.00	0.00	0.00

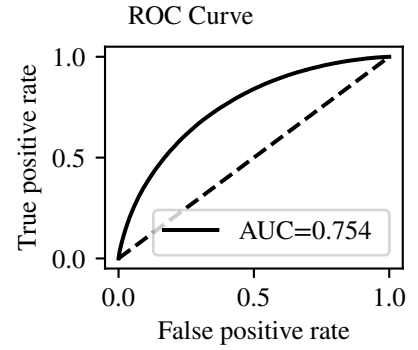
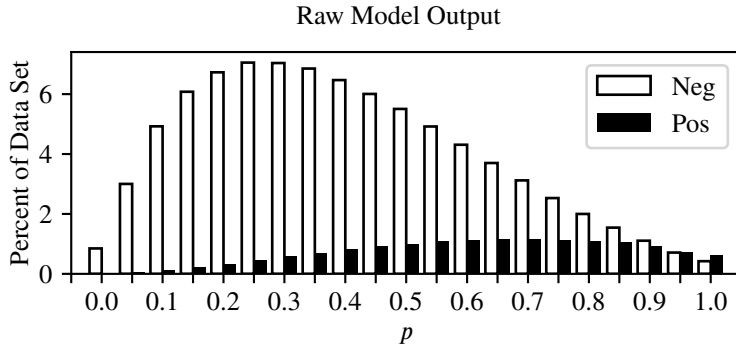


LogReg\_5\_Fold\_alpha\_balanced\_Hard\_Test\_Transformed\_100



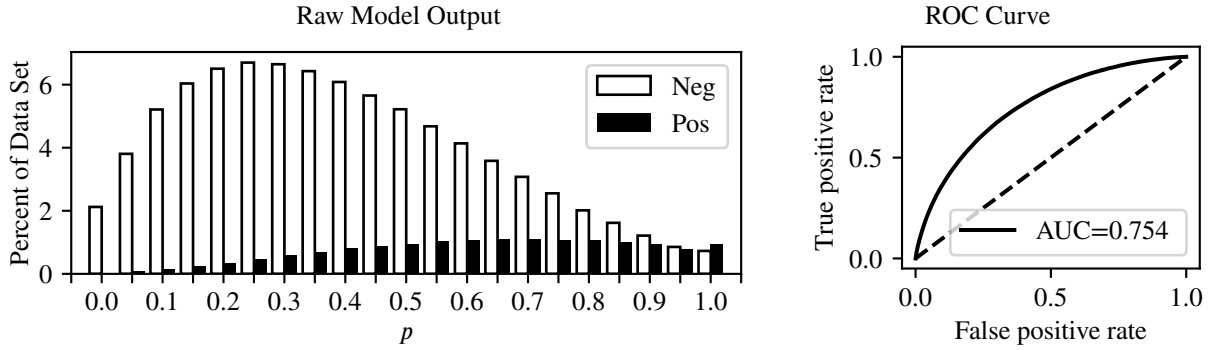
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	1	0	0.00	1	605,609	0	107,956	0.15	1.00	5.61	1.00
0.05	3,811	32	0.01	3,812	601,798	32	107,924	0.15	1.00	5.57	0.99
0.10	21,371	309	0.01	25,183	580,427	341	107,615	0.16	1.00	5.38	0.96
0.15	38,593	959	0.02	63,776	541,834	1,300	106,656	0.16	0.99	5.02	0.91
0.20	48,680	1,734	0.03	112,456	493,154	3,034	104,922	0.18	0.97	4.57	0.84
0.25	53,784	2,770	0.05	166,240	439,370	5,804	102,152	0.19	0.95	4.07	0.76
0.30	55,973	3,742	0.06	222,213	383,397	9,546	98,410	0.20	0.91	3.55	0.68
0.35	55,373	4,952	0.08	277,586	328,024	14,498	93,458	0.22	0.87	3.04	0.59
0.40	52,707	6,052	0.10	330,293	275,317	20,550	87,406	0.24	0.81	2.55	0.51
0.45	48,837	6,946	0.12	379,130	226,480	27,496	80,460	0.26	0.75	2.10	0.43
0.50	44,710	7,694	0.15	423,840	181,770	35,190	72,766	0.29	0.67	1.68	0.36
0.55	39,620	8,467	0.18	463,460	142,150	43,657	64,299	0.31	0.60	1.32	0.29
0.60	34,356	8,925	0.21	497,816	107,794	52,582	55,374	0.34	0.51	1.00	0.23
0.65	29,011	9,034	0.24	526,827	78,783	61,616	46,340	0.37	0.43	0.73	0.18
0.70	24,049	9,034	0.27	550,876	54,734	70,650	37,306	0.41	0.35	0.51	0.13
0.75	18,632	8,830	0.32	569,508	36,102	79,480	28,476	0.44	0.26	0.33	0.09
0.80	14,298	8,476	0.37	583,806	21,804	87,956	20,000	0.48	0.19	0.20	0.06
0.85	10,487	7,822	0.43	594,293	11,317	95,778	12,178	0.52	0.11	0.10	0.03
0.90	6,912	6,332	0.48	601,205	4,405	102,110	5,846	0.57	0.05	0.04	0.01
0.95	3,522	4,117	0.54	604,727	883	106,227	1,729	0.66	0.02	0.01	0.00
1.00	883	1,729	0.66	605,610	0	107,956	0	nan	0.00	0.00	0.00

LogReg\_5\_Fold\_alpha\_balanced\_Hard\_Test\_Transformed\_98



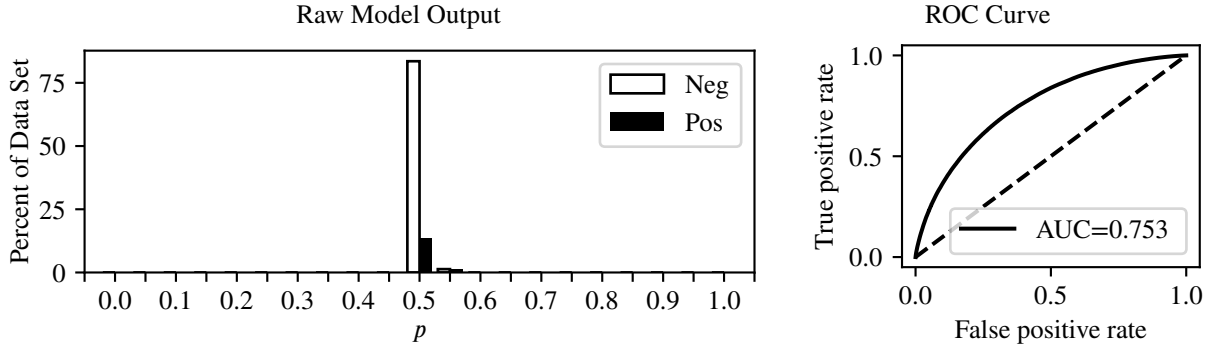
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	6,057	60	0.01	6,057	599,553	60	107,896	0.15	1.00	5.55	0.99
0.05	21,423	329	0.02	27,480	578,130	389	107,567	0.16	1.00	5.36	0.96
0.10	35,138	879	0.02	62,618	542,992	1,268	106,688	0.16	0.99	5.03	0.91
0.15	43,379	1,478	0.03	105,997	499,613	2,746	105,210	0.17	0.97	4.63	0.85
0.20	48,007	2,342	0.05	154,004	451,606	5,088	102,868	0.19	0.95	4.18	0.78
0.25	50,324	3,125	0.06	204,328	401,282	8,213	99,743	0.20	0.92	3.72	0.70
0.30	50,219	4,103	0.08	254,547	351,063	12,316	95,640	0.21	0.89	3.25	0.63
0.35	48,903	4,983	0.09	303,450	302,160	17,299	90,657	0.23	0.84	2.80	0.55
0.40	46,160	5,862	0.11	349,610	256,000	23,161	84,795	0.25	0.79	2.37	0.48
0.45	42,857	6,507	0.13	392,467	213,143	29,668	78,288	0.27	0.73	1.97	0.41
0.50	39,286	7,117	0.15	431,753	173,857	36,785	71,171	0.29	0.66	1.61	0.34
0.55	35,104	7,691	0.18	466,857	138,753	44,476	63,480	0.31	0.59	1.29	0.28
0.60	30,756	8,065	0.21	497,613	107,997	52,541	55,415	0.34	0.51	1.00	0.23
0.65	26,408	8,120	0.24	524,021	81,589	60,661	47,295	0.37	0.44	0.76	0.18
0.70	22,266	8,179	0.27	546,287	59,323	68,840	39,116	0.40	0.36	0.55	0.14
0.75	18,055	8,054	0.31	564,342	41,268	76,894	31,062	0.43	0.29	0.38	0.10
0.80	14,271	7,730	0.35	578,613	26,997	84,624	23,332	0.46	0.22	0.25	0.07
0.85	11,011	7,448	0.40	589,624	15,986	92,072	15,884	0.50	0.15	0.15	0.04
0.90	7,898	6,479	0.45	597,522	8,088	98,551	9,405	0.54	0.09	0.07	0.02
0.95	5,073	5,038	0.50	602,595	3,015	103,589	4,367	0.59	0.04	0.03	0.01
1.00	3,015	4,367	0.59	605,610	0	107,956	0	nan	0.00	0.00	0.00

LogReg\_5\_Fold\_alpha\_balanced\_Hard\_Test\_Transformed\_95



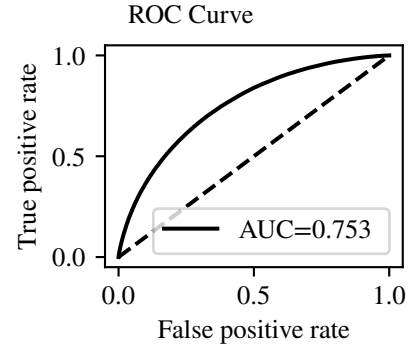
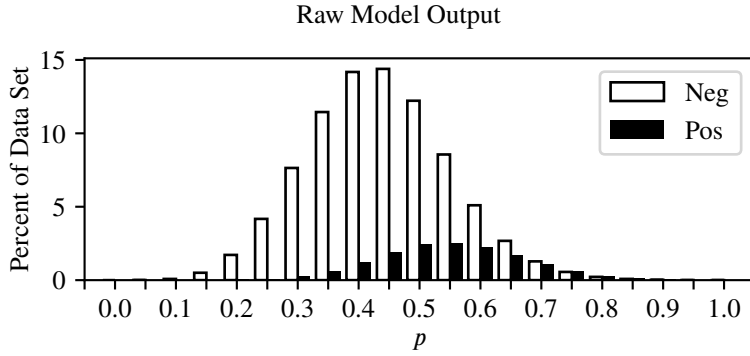
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	15,141	180	0.01	15,141	590,469	180	107,776	0.15	1.00	5.47	0.98
0.05	27,156	527	0.02	42,297	563,313	707	107,249	0.16	0.99	5.22	0.94
0.10	37,189	1,077	0.03	79,486	526,124	1,784	106,172	0.17	0.98	4.87	0.89
0.15	43,078	1,690	0.04	122,564	483,046	3,474	104,482	0.18	0.97	4.47	0.82
0.20	46,419	2,480	0.05	168,983	436,627	5,954	102,002	0.19	0.94	4.04	0.75
0.25	47,803	3,181	0.06	216,786	388,824	9,135	98,821	0.20	0.92	3.60	0.68
0.30	47,429	4,077	0.08	264,215	341,395	13,212	94,744	0.22	0.88	3.16	0.61
0.35	45,872	4,852	0.10	310,087	295,523	18,064	89,892	0.23	0.83	2.74	0.54
0.40	43,418	5,660	0.12	353,505	252,105	23,724	84,232	0.25	0.78	2.34	0.47
0.45	40,354	6,152	0.13	393,859	211,751	29,876	78,080	0.27	0.72	1.96	0.41
0.50	37,243	6,769	0.15	431,102	174,508	36,645	71,311	0.29	0.66	1.62	0.34
0.55	33,389	7,247	0.18	464,491	141,119	43,892	64,064	0.31	0.59	1.31	0.29
0.60	29,525	7,638	0.21	494,016	111,594	51,530	56,426	0.34	0.52	1.03	0.24
0.65	25,572	7,712	0.23	519,588	86,022	59,242	48,714	0.36	0.45	0.80	0.19
0.70	21,951	7,735	0.26	541,539	64,071	66,977	40,979	0.39	0.38	0.59	0.15
0.75	18,221	7,552	0.29	559,760	45,850	74,529	33,427	0.42	0.31	0.42	0.11
0.80	14,370	7,479	0.34	574,130	31,480	82,008	25,948	0.45	0.24	0.29	0.08
0.85	11,545	7,205	0.38	585,675	19,935	89,213	18,743	0.48	0.17	0.18	0.05
0.90	8,654	6,605	0.43	594,329	11,281	95,818	12,138	0.52	0.11	0.10	0.03
0.95	6,090	5,520	0.48	600,419	5,191	101,338	6,618	0.56	0.06	0.05	0.02
1.00	5,191	6,618	0.56	605,610	0	107,956	0	nan	0.00	0.00	0.00

AdaBoost\_5\_Fold\_Hard\_Test



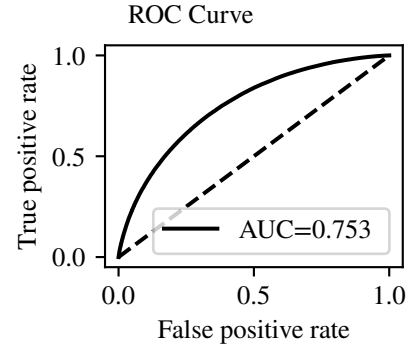
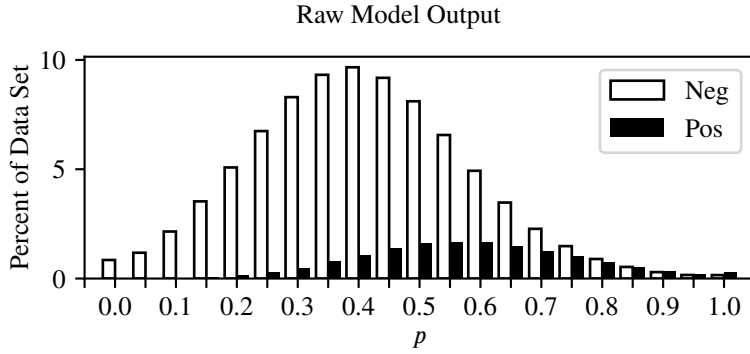
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.05	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.10	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.15	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.20	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.25	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.30	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.35	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.40	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.45	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.50	596,137	97,288	0.14	596,137	9,473	97,288	10,668	0.53	0.10	0.09	0.03
0.55	9,473	10,668	0.53	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.60	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.65	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.70	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.75	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.80	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.85	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.90	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.95	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
1.00	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00

AdaBoost\_5\_Fold\_Hard\_Test\_Transformed\_100



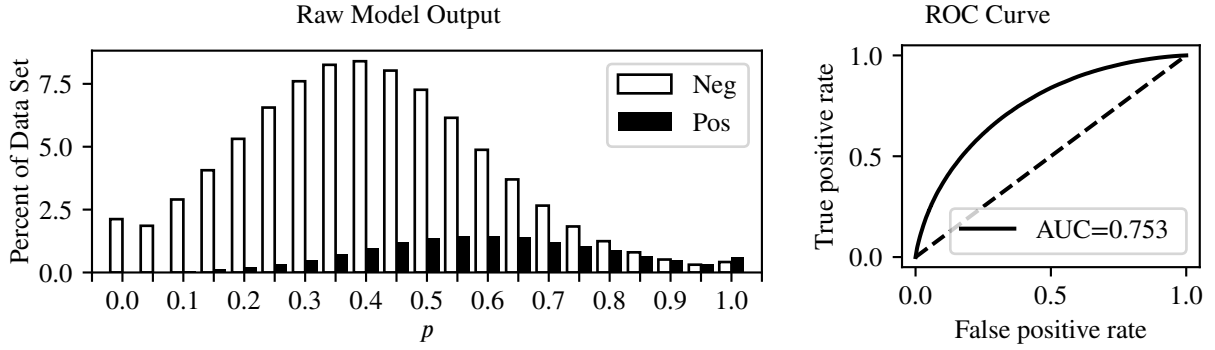
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	1	0	0.00	1	605,609	0	107,956	0.15	1.00	5.61	1.00
0.05	45	1	0.02	46	605,564	1	107,955	0.15	1.00	5.61	1.00
0.10	592	4	0.01	638	604,972	5	107,951	0.15	1.00	5.60	1.00
0.15	3,591	30	0.01	4,229	601,381	35	107,921	0.15	1.00	5.57	0.99
0.20	12,264	171	0.01	16,493	589,117	206	107,750	0.15	1.00	5.46	0.98
0.25	29,767	617	0.02	46,260	559,350	823	107,133	0.16	0.99	5.18	0.93
0.30	54,525	1,763	0.03	100,785	504,825	2,586	105,370	0.17	0.98	4.68	0.86
0.35	81,700	4,248	0.05	182,485	423,125	6,834	101,122	0.19	0.94	3.92	0.73
0.40	101,178	8,491	0.08	283,663	321,947	15,325	92,631	0.22	0.86	2.98	0.58
0.45	102,673	13,641	0.12	386,336	219,274	28,966	78,990	0.26	0.73	2.03	0.42
0.50	87,193	17,462	0.17	473,529	132,081	46,428	61,528	0.32	0.57	1.22	0.27
0.55	61,075	18,105	0.23	534,604	71,006	64,533	43,423	0.38	0.40	0.66	0.16
0.60	36,393	15,876	0.30	570,997	34,613	80,409	27,547	0.44	0.26	0.32	0.09
0.65	19,097	12,125	0.39	590,094	15,516	92,534	15,422	0.50	0.14	0.14	0.04
0.70	9,127	7,638	0.46	599,221	6,389	100,172	7,784	0.55	0.07	0.06	0.02
0.75	3,990	4,186	0.51	603,211	2,399	104,358	3,598	0.60	0.03	0.02	0.01
0.80	1,587	2,046	0.56	604,798	812	106,404	1,552	0.66	0.01	0.01	0.00
0.85	602	1,071	0.64	605,400	210	107,475	481	0.70	0.00	0.00	0.00
0.90	189	405	0.68	605,589	21	107,880	76	0.78	0.00	0.00	0.00
0.95	18	67	0.79	605,607	3	107,947	9	0.75	0.00	0.00	0.00
1.00	3	9	0.75	605,610	0	107,956	0	nan	0.00	0.00	0.00

AdaBoost\_5\_Fold\_Hard\_Test\_Transformed\_98



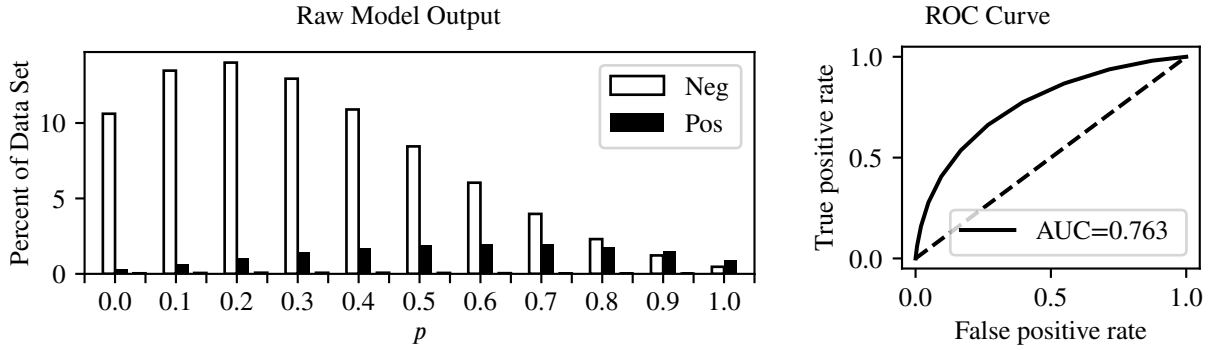
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	6,057	54	0.01	6,057	599,553	54	107,902	0.15	1.00	5.55	0.99
0.05	8,422	114	0.01	14,479	591,131	168	107,788	0.15	1.00	5.48	0.98
0.10	15,347	276	0.02	29,826	575,784	444	107,512	0.16	1.00	5.33	0.96
0.15	25,188	610	0.02	55,014	550,596	1,054	106,902	0.16	0.99	5.10	0.92
0.20	36,256	1,185	0.03	91,270	514,340	2,239	105,717	0.17	0.98	4.76	0.87
0.25	48,128	2,122	0.04	139,398	466,212	4,361	103,595	0.18	0.96	4.32	0.80
0.30	59,205	3,551	0.06	198,603	407,007	7,912	100,044	0.20	0.93	3.77	0.71
0.35	66,494	5,594	0.08	265,097	340,513	13,506	94,450	0.22	0.87	3.15	0.61
0.40	68,951	7,760	0.10	334,048	271,562	21,266	86,690	0.24	0.80	2.52	0.50
0.45	65,509	9,873	0.13	399,557	206,053	31,139	76,817	0.27	0.71	1.91	0.40
0.50	57,854	11,477	0.17	457,411	148,199	42,616	65,340	0.31	0.61	1.37	0.30
0.55	46,855	12,019	0.20	504,266	101,344	54,635	53,321	0.34	0.49	0.94	0.22
0.60	35,175	11,752	0.25	539,441	66,169	66,387	41,569	0.39	0.39	0.61	0.15
0.65	24,801	10,593	0.30	564,242	41,368	76,980	30,976	0.43	0.29	0.38	0.10
0.70	16,226	8,888	0.35	580,468	25,142	85,868	22,088	0.47	0.20	0.23	0.07
0.75	10,583	7,377	0.41	591,051	14,559	93,245	14,711	0.50	0.14	0.13	0.04
0.80	6,383	5,238	0.45	597,434	8,176	98,483	9,473	0.54	0.09	0.08	0.02
0.85	3,791	3,614	0.49	601,225	4,385	102,097	5,859	0.57	0.05	0.04	0.01
0.90	2,091	2,369	0.53	603,316	2,294	104,466	3,490	0.60	0.03	0.02	0.01
0.95	1,165	1,456	0.56	604,481	1,129	105,922	2,034	0.64	0.02	0.01	0.00
1.00	1,129	2,034	0.64	605,610	0	107,956	0	nan	0.00	0.00	0.00

AdaBoost\_5\_Fold\_Hard\_Test\_Transformed\_95



$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	15,141	173	0.01	15,141	590,469	173	107,783	0.15	1.00	5.47	0.98
0.05	13,247	246	0.02	28,388	577,222	419	107,537	0.16	1.00	5.35	0.96
0.10	20,708	480	0.02	49,096	556,514	899	107,057	0.16	0.99	5.16	0.93
0.15	29,007	866	0.03	78,103	527,507	1,765	106,191	0.17	0.98	4.89	0.89
0.20	37,912	1,446	0.04	116,015	489,595	3,211	104,745	0.18	0.97	4.54	0.83
0.25	46,794	2,460	0.05	162,809	442,801	5,671	102,285	0.19	0.95	4.10	0.76
0.30	54,257	3,621	0.06	217,066	388,544	9,292	98,664	0.20	0.91	3.60	0.68
0.35	58,916	5,271	0.08	275,982	329,628	14,563	93,393	0.22	0.87	3.05	0.59
0.40	59,937	6,951	0.10	335,919	269,691	21,514	86,442	0.24	0.80	2.50	0.50
0.45	57,283	8,588	0.13	393,202	212,408	30,102	77,854	0.27	0.72	1.97	0.41
0.50	51,839	9,802	0.16	445,041	160,569	39,904	68,052	0.30	0.63	1.49	0.32
0.55	43,884	10,461	0.19	488,925	116,685	50,365	57,591	0.33	0.53	1.08	0.24
0.60	34,805	10,376	0.23	523,730	81,880	60,741	47,215	0.37	0.44	0.76	0.18
0.65	26,402	9,935	0.27	550,132	55,478	70,676	37,280	0.40	0.35	0.51	0.13
0.70	18,973	8,730	0.32	569,105	36,505	79,406	28,550	0.44	0.26	0.34	0.09
0.75	13,056	7,471	0.36	582,161	23,449	86,877	21,079	0.47	0.20	0.22	0.06
0.80	8,881	6,368	0.42	591,042	14,568	93,245	14,711	0.50	0.14	0.13	0.04
0.85	5,720	4,624	0.45	596,762	8,848	97,869	10,087	0.53	0.09	0.08	0.03
0.90	3,673	3,468	0.49	600,435	5,175	101,337	6,619	0.56	0.06	0.05	0.02
0.95	2,207	2,350	0.52	602,642	2,968	103,687	4,269	0.59	0.04	0.03	0.01
1.00	2,968	4,269	0.59	605,610	0	107,956	0	nan	0.00	0.00	0.00

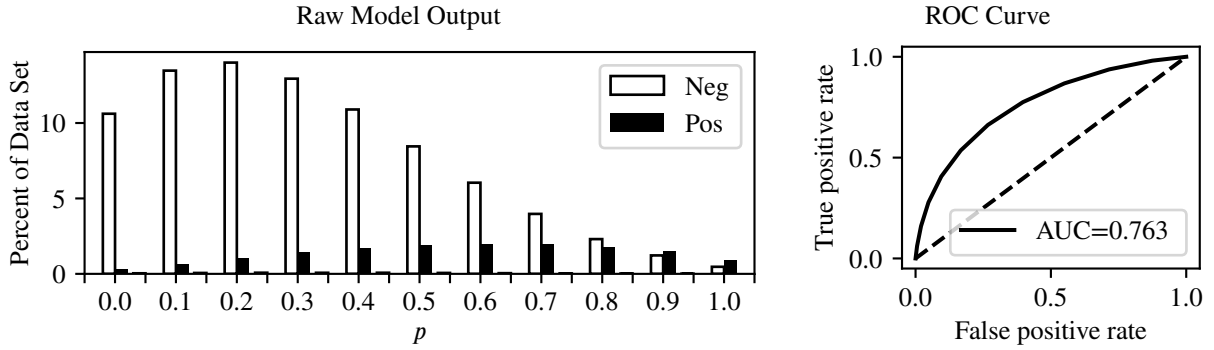
BalBag\_5\_Fold\_Hard\_Test



$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	75,744	2,072	0.03	75,744	529,866	2,072	105,884	0.17	0.98	4.91	0.89
0.05	264	4	0.01	76,008	529,602	2,076	105,880	0.17	0.98	4.91	0.89
0.10	96,139	4,663	0.05	172,147	433,463	6,739	101,217	0.19	0.94	4.02	0.75
0.15	426	26	0.06	172,573	433,037	6,765	101,191	0.19	0.94	4.01	0.75
0.20	99,937	7,461	0.07	272,510	333,100	14,226	93,730	0.22	0.87	3.09	0.60
0.25	536	39	0.07	273,046	332,564	14,265	93,691	0.22	0.87	3.08	0.60
0.30	92,329	9,999	0.10	365,375	240,235	24,264	83,692	0.26	0.78	2.23	0.45
0.35	510	68	0.12	365,885	239,725	24,332	83,624	0.26	0.77	2.22	0.45
0.40	77,756	12,130	0.13	443,641	161,969	36,462	71,494	0.31	0.66	1.50	0.33
0.45	526	95	0.15	444,167	161,443	36,557	71,399	0.31	0.66	1.50	0.33
0.50	60,301	13,559	0.18	504,468	101,142	50,116	57,840	0.36	0.54	0.94	0.22
0.55	440	121	0.22	504,908	100,702	50,237	57,719	0.36	0.53	0.93	0.22
0.60	43,121	13,830	0.24	548,029	57,581	64,067	43,889	0.43	0.41	0.53	0.14
0.65	325	121	0.27	548,354	57,256	64,188	43,768	0.43	0.41	0.53	0.14
0.70	28,360	13,739	0.33	576,714	28,896	77,927	30,029	0.51	0.28	0.27	0.08
0.75	214	136	0.39	576,928	28,682	78,063	29,893	0.51	0.28	0.27	0.08
0.80	16,441	12,611	0.43	593,369	12,241	90,674	17,282	0.59	0.16	0.11	0.04
0.85	129	102	0.44	593,498	12,112	90,776	17,180	0.59	0.16	0.11	0.04
0.90	8,726	10,552	0.55	602,224	3,386	101,328	6,628	0.66	0.06	0.03	0.01
0.95	46	63	0.58	602,270	3,340	101,391	6,565	0.66	0.06	0.03	0.01
1.00	3,340	6,565	0.66	605,610	0	107,956	0	nan	0.00	0.00	0.00

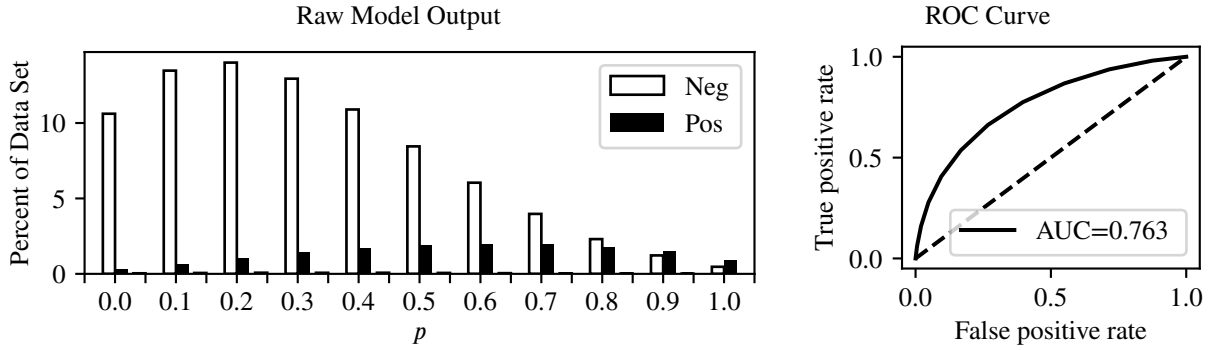


BalBag\_5\_Fold\_Hard\_Test\_Transformed\_100



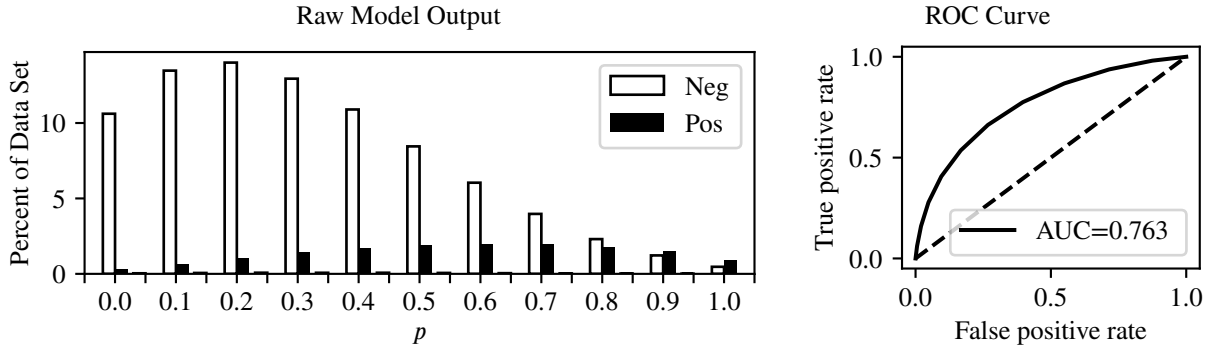
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	75,744	2,072	0.03	75,744	529,866	2,072	105,884	0.17	0.98	4.91	0.89
0.05	264	4	0.01	76,008	529,602	2,076	105,880	0.17	0.98	4.91	0.89
0.10	96,139	4,663	0.05	172,147	433,463	6,739	101,217	0.19	0.94	4.02	0.75
0.15	426	26	0.06	172,573	433,037	6,765	101,191	0.19	0.94	4.01	0.75
0.20	99,937	7,461	0.07	272,510	333,100	14,226	93,730	0.22	0.87	3.09	0.60
0.25	536	39	0.07	273,046	332,564	14,265	93,691	0.22	0.87	3.08	0.60
0.30	92,329	9,999	0.10	365,375	240,235	24,264	83,692	0.26	0.78	2.23	0.45
0.35	510	68	0.12	365,885	239,725	24,332	83,624	0.26	0.77	2.22	0.45
0.40	77,756	12,130	0.13	443,641	161,969	36,462	71,494	0.31	0.66	1.50	0.33
0.45	526	95	0.15	444,167	161,443	36,557	71,399	0.31	0.66	1.50	0.33
0.50	60,301	13,559	0.18	504,468	101,142	50,116	57,840	0.36	0.54	0.94	0.22
0.55	440	121	0.22	504,908	100,702	50,237	57,719	0.36	0.53	0.93	0.22
0.60	43,121	13,830	0.24	548,029	57,581	64,067	43,889	0.43	0.41	0.53	0.14
0.65	325	121	0.27	548,354	57,256	64,188	43,768	0.43	0.41	0.53	0.14
0.70	28,360	13,739	0.33	576,714	28,896	77,927	30,029	0.51	0.28	0.27	0.08
0.75	214	136	0.39	576,928	28,682	78,063	29,893	0.51	0.28	0.27	0.08
0.80	16,441	12,611	0.43	593,369	12,241	90,674	17,282	0.59	0.16	0.11	0.04
0.85	129	102	0.44	593,498	12,112	90,776	17,180	0.59	0.16	0.11	0.04
0.90	8,726	10,552	0.55	602,224	3,386	101,328	6,628	0.66	0.06	0.03	0.01
0.95	46	63	0.58	602,270	3,340	101,391	6,565	0.66	0.06	0.03	0.01
1.00	3,340	6,565	0.66	605,610	0	107,956	0	nan	0.00	0.00	0.00

BalBag\_5\_Fold\_Hard\_Test\_Transformed\_98



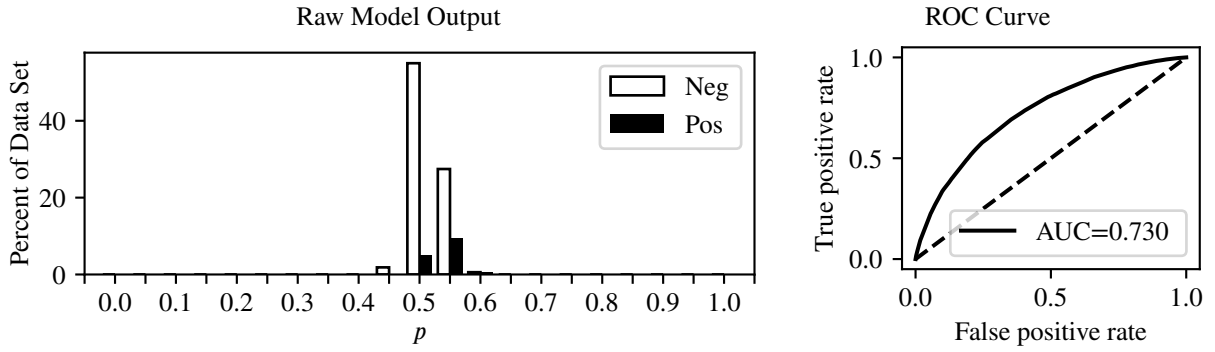
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	75,744	2,072	0.03	75,744	529,866	2,072	105,884	0.17	0.98	4.91	0.89
0.05	264	4	0.01	76,008	529,602	2,076	105,880	0.17	0.98	4.91	0.89
0.10	96,139	4,663	0.05	172,147	433,463	6,739	101,217	0.19	0.94	4.02	0.75
0.15	426	26	0.06	172,573	433,037	6,765	101,191	0.19	0.94	4.01	0.75
0.20	99,937	7,461	0.07	272,510	333,100	14,226	93,730	0.22	0.87	3.09	0.60
0.25	536	39	0.07	273,046	332,564	14,265	93,691	0.22	0.87	3.08	0.60
0.30	92,329	9,999	0.10	365,375	240,235	24,264	83,692	0.26	0.78	2.23	0.45
0.35	510	68	0.12	365,885	239,725	24,332	83,624	0.26	0.77	2.22	0.45
0.40	77,756	12,130	0.13	443,641	161,969	36,462	71,494	0.31	0.66	1.50	0.33
0.45	526	95	0.15	444,167	161,443	36,557	71,399	0.31	0.66	1.50	0.33
0.50	60,301	13,559	0.18	504,468	101,142	50,116	57,840	0.36	0.54	0.94	0.22
0.55	440	121	0.22	504,908	100,702	50,237	57,719	0.36	0.53	0.93	0.22
0.60	43,121	13,830	0.24	548,029	57,581	64,067	43,889	0.43	0.41	0.53	0.14
0.65	325	121	0.27	548,354	57,256	64,188	43,768	0.43	0.41	0.53	0.14
0.70	28,360	13,739	0.33	576,714	28,896	77,927	30,029	0.51	0.28	0.27	0.08
0.75	214	136	0.39	576,928	28,682	78,063	29,893	0.51	0.28	0.27	0.08
0.80	16,441	12,611	0.43	593,369	12,241	90,674	17,282	0.59	0.16	0.11	0.04
0.85	129	102	0.44	593,498	12,112	90,776	17,180	0.59	0.16	0.11	0.04
0.90	8,726	10,552	0.55	602,224	3,386	101,328	6,628	0.66	0.06	0.03	0.01
0.95	46	63	0.58	602,270	3,340	101,391	6,565	0.66	0.06	0.03	0.01
1.00	3,340	6,565	0.66	605,610	0	107,956	0	nan	0.00	0.00	0.00

BalBag\_5\_Fold\_Hard\_Test\_Transformed\_95



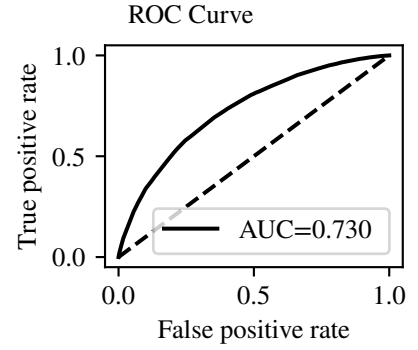
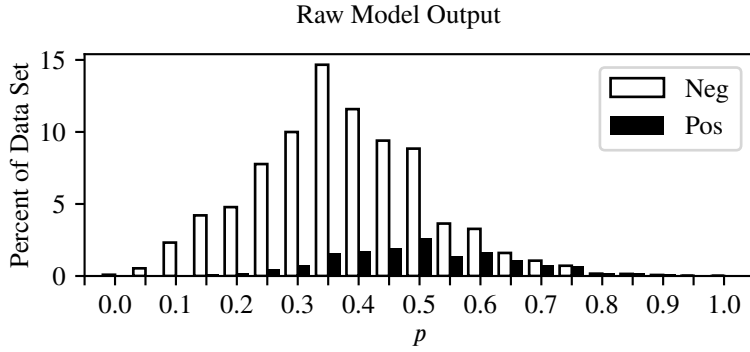
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	75,744	2,072	0.03	75,744	529,866	2,072	105,884	0.17	0.98	4.91	0.89
0.05	264	4	0.01	76,008	529,602	2,076	105,880	0.17	0.98	4.91	0.89
0.10	96,139	4,663	0.05	172,147	433,463	6,739	101,217	0.19	0.94	4.02	0.75
0.15	426	26	0.06	172,573	433,037	6,765	101,191	0.19	0.94	4.01	0.75
0.20	99,937	7,461	0.07	272,510	333,100	14,226	93,730	0.22	0.87	3.09	0.60
0.25	536	39	0.07	273,046	332,564	14,265	93,691	0.22	0.87	3.08	0.60
0.30	92,329	9,999	0.10	365,375	240,235	24,264	83,692	0.26	0.78	2.23	0.45
0.35	510	68	0.12	365,885	239,725	24,332	83,624	0.26	0.77	2.22	0.45
0.40	77,756	12,130	0.13	443,641	161,969	36,462	71,494	0.31	0.66	1.50	0.33
0.45	526	95	0.15	444,167	161,443	36,557	71,399	0.31	0.66	1.50	0.33
0.50	60,301	13,559	0.18	504,468	101,142	50,116	57,840	0.36	0.54	0.94	0.22
0.55	440	121	0.22	504,908	100,702	50,237	57,719	0.36	0.53	0.93	0.22
0.60	43,121	13,830	0.24	548,029	57,581	64,067	43,889	0.43	0.41	0.53	0.14
0.65	325	121	0.27	548,354	57,256	64,188	43,768	0.43	0.41	0.53	0.14
0.70	28,360	13,739	0.33	576,714	28,896	77,927	30,029	0.51	0.28	0.27	0.08
0.75	214	136	0.39	576,928	28,682	78,063	29,893	0.51	0.28	0.27	0.08
0.80	16,441	12,611	0.43	593,369	12,241	90,674	17,282	0.59	0.16	0.11	0.04
0.85	129	102	0.44	593,498	12,112	90,776	17,180	0.59	0.16	0.11	0.04
0.90	8,726	10,552	0.55	602,224	3,386	101,328	6,628	0.66	0.06	0.03	0.01
0.95	46	63	0.58	602,270	3,340	101,391	6,565	0.66	0.06	0.03	0.01
1.00	3,340	6,565	0.66	605,610	0	107,956	0	nan	0.00	0.00	0.00

EEC\_5\_Fold\_Hard\_Test



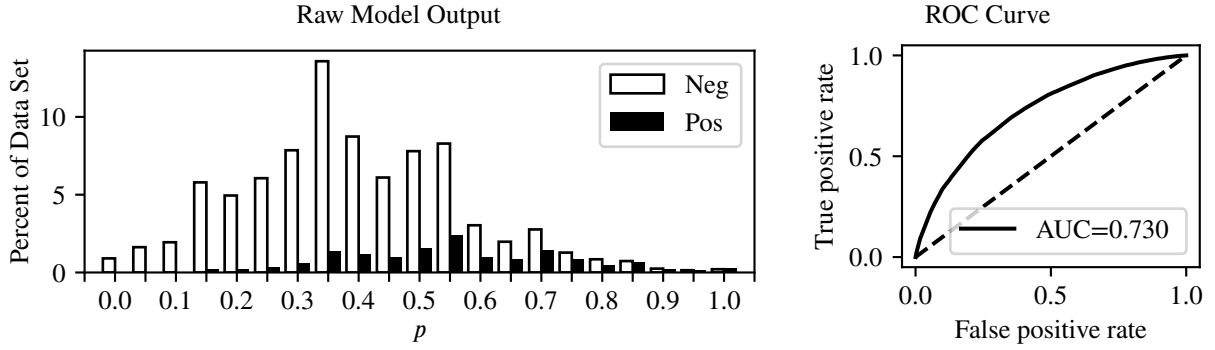
	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
p											
0.00	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.05	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.10	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.15	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.20	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.25	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.30	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.35	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.40	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.45	13,212	237	0.02	13,212	592,398	237	107,719	0.15	1.00	5.49	0.98
0.50	392,319	35,493	0.08	405,531	200,079	35,730	72,226	0.27	0.67	1.85	0.38
0.55	195,857	67,742	0.26	601,388	4,222	103,472	4,484	0.52	0.04	0.04	0.01
0.60	4,222	4,484	0.52	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.65	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.70	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.75	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.80	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.85	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.90	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.95	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
1.00	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00

EEC\_5\_Fold\_Hard\_Test\_Transformed\_100



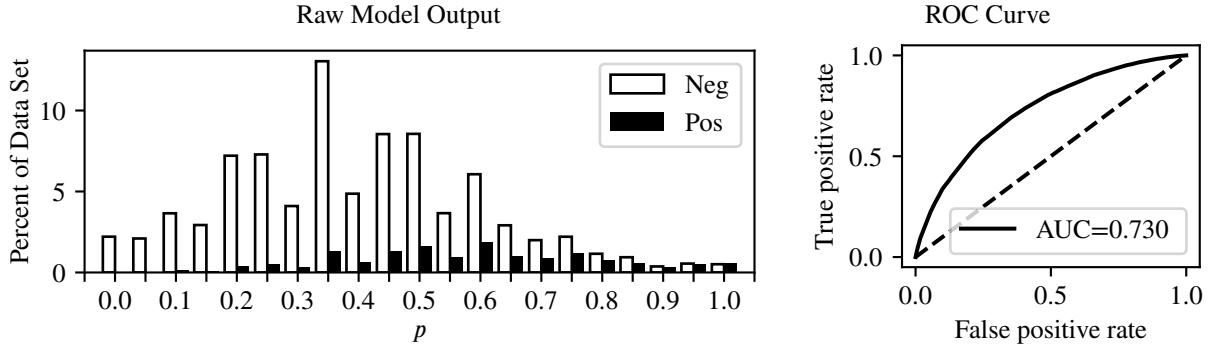
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	628	4	0.01	628	604,982	4	107,952	0.15	1.00	5.60	1.00
0.05	3,803	41	0.01	4,431	601,179	45	107,911	0.15	1.00	5.57	0.99
0.10	16,555	339	0.02	20,986	584,624	384	107,572	0.16	1.00	5.42	0.97
0.15	30,033	960	0.03	51,019	554,591	1,344	106,612	0.16	0.99	5.14	0.93
0.20	34,122	1,342	0.04	85,141	520,469	2,686	105,270	0.17	0.98	4.82	0.88
0.25	55,446	3,059	0.05	140,587	465,023	5,745	102,211	0.18	0.95	4.31	0.79
0.30	71,324	5,324	0.07	211,911	393,699	11,069	96,887	0.20	0.90	3.65	0.69
0.35	104,641	11,079	0.10	316,552	289,058	22,148	85,808	0.23	0.79	2.68	0.53
0.40	82,657	12,385	0.13	399,209	206,401	34,533	73,423	0.26	0.68	1.91	0.39
0.45	67,061	13,451	0.17	466,270	139,340	47,984	59,972	0.30	0.56	1.29	0.28
0.50	63,095	18,538	0.23	529,365	76,245	66,522	41,434	0.35	0.38	0.71	0.16
0.55	25,981	9,479	0.27	555,346	50,264	76,001	31,955	0.39	0.30	0.47	0.12
0.60	23,343	11,468	0.33	578,689	26,921	87,469	20,487	0.43	0.19	0.25	0.07
0.65	11,422	7,503	0.40	590,111	15,499	94,972	12,984	0.46	0.12	0.14	0.04
0.70	7,595	5,066	0.40	597,706	7,904	100,038	7,918	0.50	0.07	0.07	0.02
0.75	5,080	4,749	0.48	602,786	2,824	104,787	3,169	0.53	0.03	0.03	0.01
0.80	1,164	1,098	0.49	603,950	1,660	105,885	2,071	0.56	0.02	0.02	0.01
0.85	1,040	1,166	0.53	604,990	620	107,051	905	0.59	0.01	0.01	0.00
0.90	515	768	0.60	605,505	105	107,819	137	0.57	0.00	0.00	0.00
0.95	76	108	0.59	605,581	29	107,927	29	0.50	0.00	0.00	0.00
1.00	29	29	0.50	605,610	0	107,956	0	nan	0.00	0.00	0.00

EEC\_5\_Fold\_Hard\_Test\_Transformed\_98



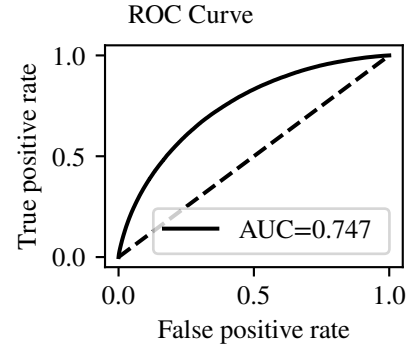
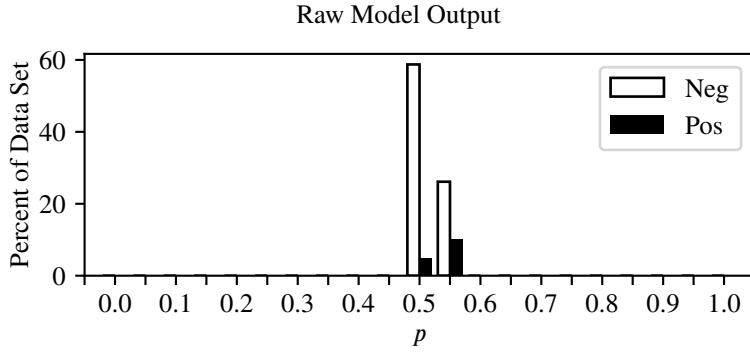
	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
p											
0.00	6,466	100	0.02	6,466	599,144	100	107,856	0.15	1.00	5.55	0.99
0.05	11,604	228	0.02	18,070	587,540	328	107,628	0.15	1.00	5.44	0.97
0.10	13,863	353	0.02	31,933	573,677	681	107,275	0.16	0.99	5.31	0.95
0.15	41,323	1,403	0.03	73,256	532,354	2,084	105,872	0.17	0.98	4.93	0.89
0.20	35,306	1,791	0.05	108,562	497,048	3,875	104,081	0.17	0.96	4.60	0.84
0.25	43,239	2,662	0.06	151,801	453,809	6,537	101,419	0.18	0.94	4.20	0.78
0.30	56,056	4,191	0.07	207,857	397,753	10,728	97,228	0.20	0.90	3.68	0.69
0.35	96,894	10,009	0.09	304,751	300,859	20,737	87,219	0.22	0.81	2.79	0.54
0.40	62,351	8,651	0.12	367,102	238,508	29,388	78,568	0.25	0.73	2.21	0.44
0.45	43,554	7,316	0.14	410,656	194,954	36,704	71,252	0.27	0.66	1.81	0.37
0.50	55,648	11,287	0.17	466,304	139,306	47,991	59,965	0.30	0.56	1.29	0.28
0.55	59,127	17,004	0.22	525,431	80,179	64,995	42,961	0.35	0.40	0.74	0.17
0.60	21,652	7,183	0.25	547,083	58,527	72,178	35,778	0.38	0.33	0.54	0.13
0.65	14,100	6,294	0.31	561,183	44,427	78,472	29,484	0.40	0.27	0.41	0.10
0.70	19,745	10,422	0.35	580,928	24,682	88,894	19,062	0.44	0.18	0.23	0.06
0.75	9,121	6,020	0.40	590,049	15,561	94,914	13,042	0.46	0.12	0.14	0.04
0.80	6,050	3,653	0.38	596,099	9,511	98,567	9,389	0.50	0.09	0.09	0.03
0.85	5,233	4,869	0.48	601,332	4,278	103,436	4,520	0.51	0.04	0.04	0.01
0.90	1,765	1,644	0.48	603,097	2,513	105,080	2,876	0.53	0.03	0.02	0.01
0.95	1,031	954	0.48	604,128	1,482	106,034	1,922	0.56	0.02	0.01	0.00
1.00	1,482	1,922	0.56	605,610	0	107,956	0	nan	0.00	0.00	0.00

EEC\_5\_Fold\_Hard\_Test\_Transformed\_95



$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	15,773	279	0.02	15,773	589,837	279	107,677	0.15	1.00	5.46	0.98
0.05	14,974	371	0.02	30,747	574,863	650	107,306	0.16	0.99	5.32	0.96
0.10	26,076	915	0.03	56,823	548,787	1,565	106,391	0.16	0.99	5.08	0.92
0.15	20,903	734	0.03	77,726	527,884	2,299	105,657	0.17	0.98	4.89	0.89
0.20	51,447	2,790	0.05	129,173	476,437	5,089	102,867	0.18	0.95	4.41	0.81
0.25	52,003	3,519	0.06	181,176	424,434	8,608	99,348	0.19	0.92	3.93	0.73
0.30	29,272	2,322	0.07	210,448	395,162	10,930	97,026	0.20	0.90	3.66	0.69
0.35	93,068	9,621	0.09	303,516	302,094	20,551	87,405	0.22	0.81	2.80	0.55
0.40	34,707	4,600	0.12	338,223	267,387	25,151	82,805	0.24	0.77	2.48	0.49
0.45	60,969	9,378	0.13	399,192	206,418	34,529	73,427	0.26	0.68	1.91	0.39
0.50	61,069	11,821	0.16	460,261	145,349	46,350	61,606	0.30	0.57	1.35	0.29
0.55	26,127	6,980	0.21	486,388	119,222	53,330	54,626	0.31	0.51	1.10	0.24
0.60	43,280	13,284	0.23	529,668	75,942	66,614	41,342	0.35	0.38	0.70	0.16
0.65	20,783	7,136	0.26	550,451	55,159	73,750	34,206	0.38	0.32	0.51	0.13
0.70	14,246	6,347	0.31	564,697	40,913	80,097	27,859	0.41	0.26	0.38	0.10
0.75	15,748	8,488	0.35	580,445	25,165	88,585	19,371	0.43	0.18	0.23	0.06
0.80	8,244	5,298	0.39	588,689	16,921	93,883	14,073	0.45	0.13	0.16	0.04
0.85	6,712	4,251	0.39	595,401	10,209	98,134	9,822	0.49	0.09	0.09	0.03
0.90	2,656	2,212	0.45	598,057	7,553	100,346	7,610	0.50	0.07	0.07	0.02
0.95	3,920	3,630	0.48	601,977	3,633	103,976	3,980	0.52	0.04	0.03	0.01
1.00	3,633	3,980	0.52	605,610	0	107,956	0	nan	0.00	0.00	0.00

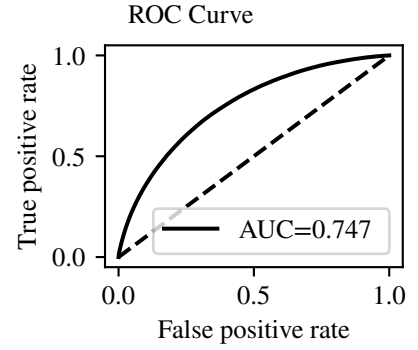
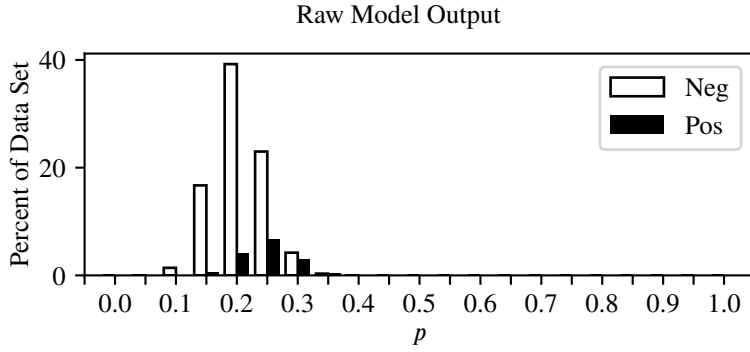
RUSBoost\_5\_Fold\_Hard\_Test



$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.05	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.10	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.15	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.20	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.25	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.30	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.35	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.40	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.45	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.50	419,145	35,405	0.08	419,145	186,465	35,405	72,551	0.28	0.67	1.73	0.36
0.55	186,465	72,551	0.28	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.60	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.65	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.70	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.75	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.80	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.85	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.90	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.95	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
1.00	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00

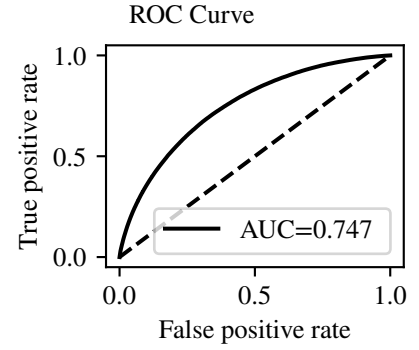
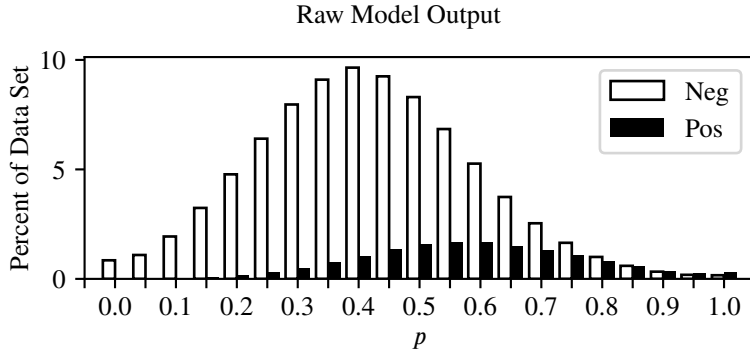


RUSBoost\_5\_Fold\_Hard\_Test\_Transformed\_100



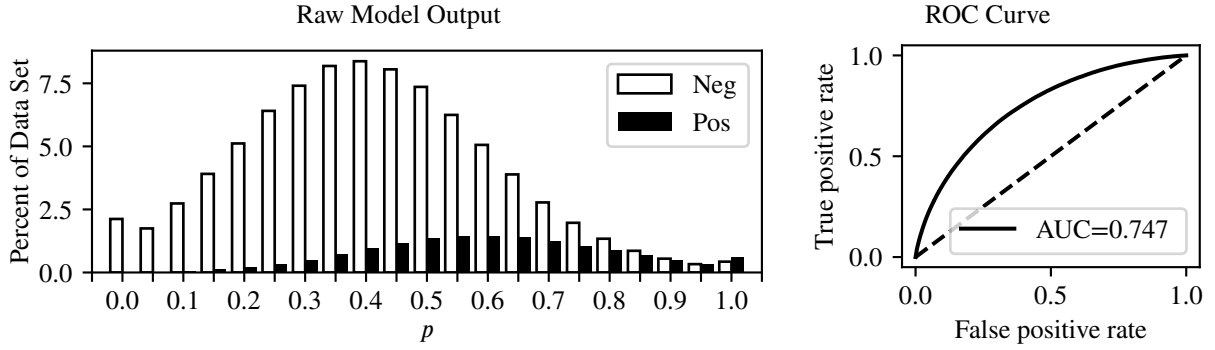
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	1	0	0.00	1	605,609	0	107,956	0.15	1.00	5.61	1.00
0.05	77	1	0.01	78	605,532	1	107,955	0.15	1.00	5.61	1.00
0.10	10,027	146	0.01	10,105	595,505	147	107,809	0.15	1.00	5.52	0.99
0.15	119,192	4,031	0.03	129,297	476,313	4,178	103,778	0.18	0.96	4.41	0.81
0.20	279,846	29,404	0.10	409,143	196,467	33,582	74,374	0.27	0.69	1.82	0.38
0.25	164,039	48,687	0.23	573,182	32,428	82,269	25,687	0.44	0.24	0.30	0.08
0.30	30,072	22,133	0.42	603,254	2,356	104,402	3,554	0.60	0.03	0.02	0.01
0.35	2,329	3,456	0.60	605,583	27	107,858	98	0.78	0.00	0.00	0.00
0.40	25	95	0.79	605,608	2	107,953	3	0.60	0.00	0.00	0.00
0.45	0	0	nan	605,608	2	107,953	3	0.60	0.00	0.00	0.00
0.50	0	0	nan	605,608	2	107,953	3	0.60	0.00	0.00	0.00
0.55	0	0	nan	605,608	2	107,953	3	0.60	0.00	0.00	0.00
0.60	0	0	nan	605,608	2	107,953	3	0.60	0.00	0.00	0.00
0.65	0	0	nan	605,608	2	107,953	3	0.60	0.00	0.00	0.00
0.70	0	0	nan	605,608	2	107,953	3	0.60	0.00	0.00	0.00
0.75	0	0	nan	605,608	2	107,953	3	0.60	0.00	0.00	0.00
0.80	0	0	nan	605,608	2	107,953	3	0.60	0.00	0.00	0.00
0.85	2	0	0.00	605,610	0	107,953	3	1.00	0.00	0.00	0.00
0.90	0	0	nan	605,610	0	107,953	3	1.00	0.00	0.00	0.00
0.95	0	2	1.00	605,610	0	107,955	1	1.00	0.00	0.00	0.00
1.00	0	1	1.00	605,610	0	107,956	0	nan	0.00	0.00	0.00

RUSBoost\_5\_Fold\_Hard\_Test\_Transformed\_98



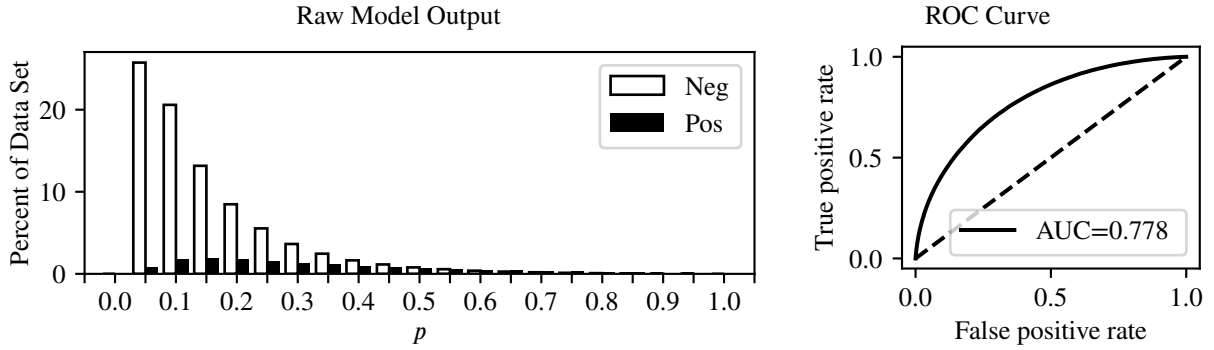
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	6,057	86	0.01	6,057	599,553	86	107,870	0.15	1.00	5.55	0.99
0.05	7,787	119	0.02	13,844	591,766	205	107,751	0.15	1.00	5.48	0.98
0.10	13,814	291	0.02	27,658	577,952	496	107,460	0.16	1.00	5.35	0.96
0.15	23,122	580	0.02	50,780	554,830	1,076	106,880	0.16	0.99	5.14	0.93
0.20	34,069	1,158	0.03	84,849	520,761	2,234	105,722	0.17	0.98	4.82	0.88
0.25	45,690	2,004	0.04	130,539	475,071	4,238	103,718	0.18	0.96	4.40	0.81
0.30	56,830	3,345	0.06	187,369	418,241	7,583	100,373	0.19	0.93	3.87	0.73
0.35	64,926	5,310	0.08	252,295	353,315	12,893	95,063	0.21	0.88	3.27	0.63
0.40	68,843	7,452	0.10	321,138	284,472	20,345	87,611	0.24	0.81	2.64	0.52
0.45	66,004	9,492	0.13	387,142	218,468	29,837	78,119	0.26	0.72	2.02	0.42
0.50	59,244	11,211	0.16	446,386	159,224	41,048	66,908	0.30	0.62	1.47	0.32
0.55	48,830	11,937	0.20	495,216	110,394	52,985	54,971	0.33	0.51	1.02	0.23
0.60	37,560	11,862	0.24	532,776	72,834	64,847	43,109	0.37	0.40	0.67	0.16
0.65	26,689	10,654	0.29	559,465	46,145	75,501	32,455	0.41	0.30	0.43	0.11
0.70	18,121	9,190	0.34	577,586	28,024	84,691	23,265	0.45	0.22	0.26	0.07
0.75	11,757	7,575	0.39	589,343	16,267	92,266	15,690	0.49	0.15	0.15	0.04
0.80	7,149	5,582	0.44	596,492	9,118	97,848	10,108	0.53	0.09	0.08	0.03
0.85	4,254	3,942	0.48	600,746	4,864	101,790	6,166	0.56	0.06	0.05	0.02
0.90	2,353	2,422	0.51	603,099	2,511	104,212	3,744	0.60	0.03	0.02	0.01
0.95	1,325	1,634	0.55	604,424	1,186	105,846	2,110	0.64	0.02	0.01	0.00
1.00	1,186	2,110	0.64	605,610	0	107,956	0	nan	0.00	0.00	0.00

RUSBoost\_5\_Fold\_Hard\_Test\_Transformed\_95



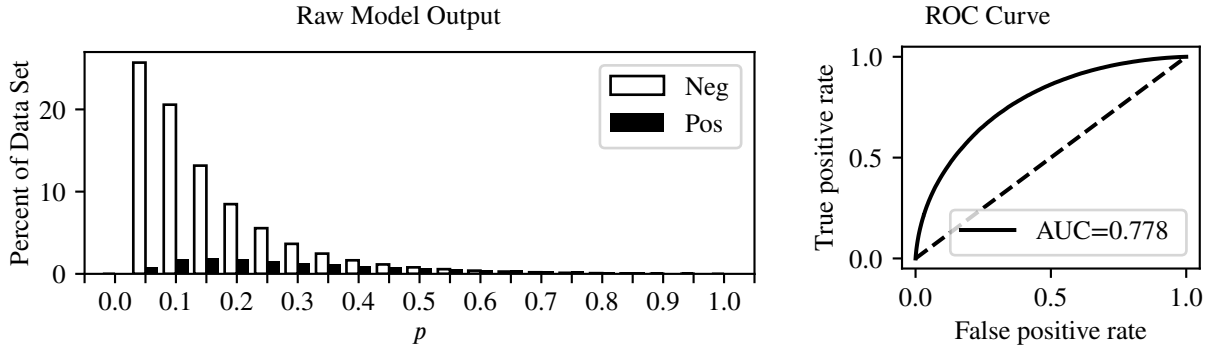
	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
$p$											
0.00	15,141	235	0.02	15,141	590,469	235	107,721	0.15	1.00	5.47	0.98
0.05	12,465	260	0.02	27,606	578,004	495	107,461	0.16	1.00	5.35	0.96
0.10	19,533	485	0.02	47,139	558,471	980	106,976	0.16	0.99	5.17	0.93
0.15	27,895	889	0.03	75,034	530,576	1,869	106,087	0.17	0.98	4.91	0.89
0.20	36,506	1,489	0.04	111,540	494,070	3,358	104,598	0.17	0.97	4.58	0.84
0.25	45,727	2,284	0.05	157,267	448,343	5,642	102,314	0.19	0.95	4.15	0.77
0.30	52,840	3,612	0.06	210,107	395,503	9,254	98,702	0.20	0.91	3.66	0.69
0.35	58,427	5,198	0.08	268,534	337,076	14,452	93,504	0.22	0.87	3.12	0.60
0.40	59,773	6,820	0.10	328,307	277,303	21,272	86,684	0.24	0.80	2.57	0.51
0.45	57,473	8,369	0.13	385,780	219,830	29,641	78,315	0.26	0.73	2.04	0.42
0.50	52,512	9,717	0.16	438,292	167,318	39,358	68,598	0.29	0.64	1.55	0.33
0.55	44,582	10,361	0.19	482,874	122,736	49,719	58,237	0.32	0.54	1.14	0.25
0.60	36,099	10,452	0.22	518,973	86,637	60,171	47,785	0.36	0.44	0.80	0.19
0.65	27,746	9,917	0.26	546,719	58,891	70,088	37,868	0.39	0.35	0.55	0.14
0.70	19,821	8,788	0.31	566,540	39,070	78,876	29,080	0.43	0.27	0.36	0.10
0.75	14,056	7,594	0.35	580,596	25,014	86,470	21,486	0.46	0.20	0.23	0.07
0.80	9,551	6,385	0.40	590,147	15,463	92,855	15,101	0.49	0.14	0.14	0.04
0.85	6,133	4,807	0.44	596,280	9,330	97,662	10,294	0.52	0.10	0.09	0.03
0.90	3,911	3,628	0.48	600,191	5,419	101,290	6,666	0.55	0.06	0.05	0.02
0.95	2,359	2,346	0.50	602,550	3,060	103,636	4,320	0.59	0.04	0.03	0.01
1.00	3,060	4,320	0.59	605,610	0	107,956	0	nan	0.00	0.00	0.00

KBFC\_5\_Fold\_alpha\_0\_5\_gamma\_0\_0\_Hard\_Test



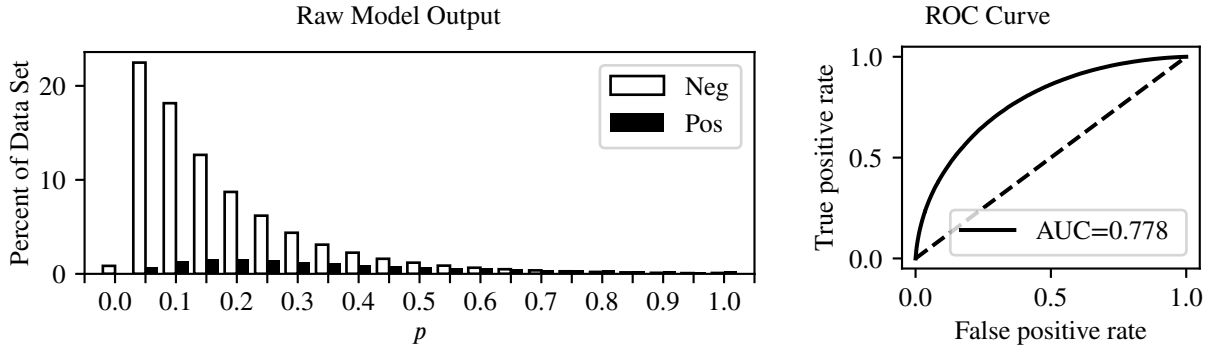
	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
p											
0.00	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.05	183,652	5,640	0.03	183,652	421,958	5,640	102,316	0.20	0.95	3.91	0.73
0.10	146,917	12,210	0.08	330,569	275,041	17,850	90,106	0.25	0.83	2.55	0.51
0.15	93,929	13,593	0.13	424,498	181,112	31,443	76,513	0.30	0.71	1.68	0.36
0.20	60,492	12,911	0.18	484,990	120,620	44,354	63,602	0.35	0.59	1.12	0.26
0.25	39,520	11,218	0.22	524,510	81,100	55,572	52,384	0.39	0.49	0.75	0.19
0.30	25,961	9,464	0.27	550,471	55,139	65,036	42,920	0.44	0.40	0.51	0.14
0.35	17,517	7,909	0.31	567,988	37,622	72,945	35,011	0.48	0.32	0.35	0.10
0.40	11,735	6,616	0.36	579,723	25,887	79,561	28,395	0.52	0.26	0.24	0.08
0.45	8,178	5,743	0.41	587,901	17,709	85,304	22,652	0.56	0.21	0.16	0.06
0.50	5,611	4,808	0.46	593,512	12,098	90,112	17,844	0.60	0.17	0.11	0.04
0.55	4,041	4,092	0.50	597,553	8,057	94,204	13,752	0.63	0.13	0.07	0.03
0.60	2,760	3,471	0.56	600,313	5,297	97,675	10,281	0.66	0.10	0.05	0.02
0.65	1,971	2,892	0.59	602,284	3,326	100,567	7,389	0.69	0.07	0.03	0.02
0.70	1,376	2,438	0.64	603,660	1,950	103,005	4,951	0.72	0.05	0.02	0.01
0.75	890	2,020	0.69	604,550	1,060	105,025	2,931	0.73	0.03	0.01	0.01
0.80	602	1,452	0.71	605,152	458	106,477	1,479	0.76	0.01	0.00	0.00
0.85	313	896	0.74	605,465	145	107,373	583	0.80	0.01	0.00	0.00
0.90	118	420	0.78	605,583	27	107,793	163	0.86	0.00	0.00	0.00
0.95	27	123	0.82	605,610	0	107,916	40	1.00	0.00	0.00	0.00
1.00	0	40	1.00	605,610	0	107,956	0	nan	0.00	0.00	0.00

KBFC\_5\_Fold\_alpha\_0\_5\_gamma\_0\_0\_Hard\_Test\_Transformed\_100



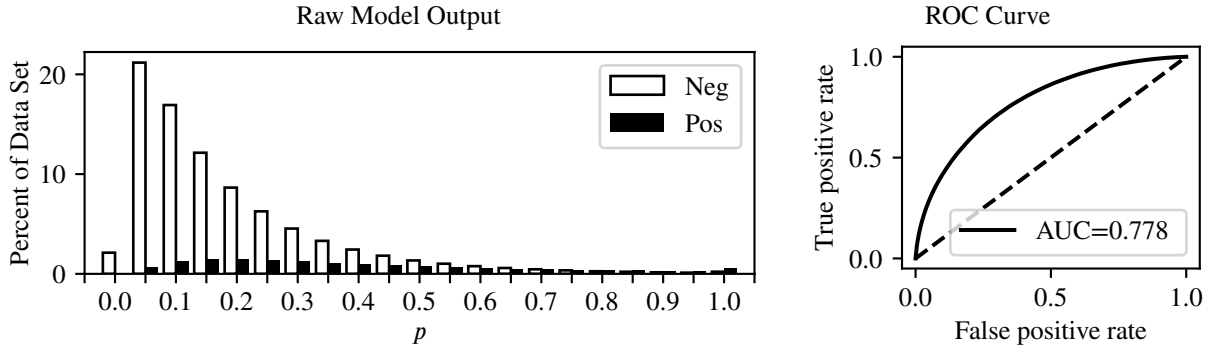
	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
$p$											
0.00	1	0	0.00	1	605,609	0	107,956	0.15	1.00	5.61	1.00
0.05	183,331	5,620	0.03	183,332	422,278	5,620	102,336	0.20	0.95	3.91	0.74
0.10	146,814	12,169	0.08	330,146	275,464	17,789	90,167	0.25	0.84	2.55	0.51
0.15	93,933	13,588	0.13	424,079	181,531	31,377	76,579	0.30	0.71	1.68	0.36
0.20	60,495	12,897	0.18	484,574	121,036	44,274	63,682	0.34	0.59	1.12	0.26
0.25	39,641	11,205	0.22	524,215	81,395	55,479	52,477	0.39	0.49	0.75	0.19
0.30	26,032	9,469	0.27	550,247	55,363	64,948	43,008	0.44	0.40	0.51	0.14
0.35	17,570	7,903	0.31	567,817	37,793	72,851	35,105	0.48	0.33	0.35	0.10
0.40	11,767	6,632	0.36	579,584	26,026	79,483	28,473	0.52	0.26	0.24	0.08
0.45	8,191	5,711	0.41	587,775	17,835	85,194	22,762	0.56	0.21	0.17	0.06
0.50	5,639	4,836	0.46	593,414	12,196	90,030	17,926	0.60	0.17	0.11	0.04
0.55	4,062	4,103	0.50	597,476	8,134	94,133	13,823	0.63	0.13	0.08	0.03
0.60	2,787	3,470	0.55	600,263	5,347	97,603	10,353	0.66	0.10	0.05	0.02
0.65	1,982	2,889	0.59	602,245	3,365	100,492	7,464	0.69	0.07	0.03	0.02
0.70	1,382	2,447	0.64	603,627	1,983	102,939	5,017	0.72	0.05	0.02	0.01
0.75	900	2,034	0.69	604,527	1,083	104,973	2,983	0.73	0.03	0.01	0.01
0.80	615	1,483	0.71	605,142	468	106,456	1,500	0.76	0.01	0.00	0.00
0.85	315	900	0.74	605,457	153	107,356	600	0.80	0.01	0.00	0.00
0.90	124	432	0.78	605,581	29	107,788	168	0.85	0.00	0.00	0.00
0.95	29	127	0.81	605,610	0	107,915	41	1.00	0.00	0.00	0.00
1.00	0	41	1.00	605,610	0	107,956	0	nan	0.00	0.00	0.00

KBFC\_5\_Fold\_alpha\_0\_5\_gamma\_0\_0\_Hard\_Test\_Transformed\_98



p	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	6,057	49	0.01	6,057	599,553	49	107,907	0.15	1.00	5.55	0.99
0.05	160,368	4,630	0.03	166,425	439,185	4,679	103,277	0.19	0.96	4.07	0.76
0.10	129,548	9,429	0.07	295,973	309,637	14,108	93,848	0.23	0.87	2.87	0.57
0.15	90,311	11,021	0.11	386,284	219,326	25,129	82,827	0.27	0.77	2.03	0.42
0.20	62,194	10,920	0.15	448,478	157,132	36,049	71,907	0.31	0.67	1.46	0.32
0.25	44,170	10,311	0.19	492,648	112,962	46,360	61,596	0.35	0.57	1.05	0.24
0.30	31,203	9,021	0.22	523,851	81,759	55,381	52,575	0.39	0.49	0.76	0.19
0.35	22,161	7,876	0.26	546,012	59,598	63,257	44,699	0.43	0.41	0.55	0.15
0.40	16,075	6,732	0.30	562,087	43,523	69,989	37,967	0.47	0.35	0.40	0.11
0.45	11,440	5,930	0.34	573,527	32,083	75,919	32,037	0.50	0.30	0.30	0.09
0.50	8,487	5,138	0.38	582,014	23,596	81,057	26,899	0.53	0.25	0.22	0.07
0.55	6,243	4,532	0.42	588,257	17,353	85,589	22,367	0.56	0.21	0.16	0.06
0.60	4,646	3,917	0.46	592,903	12,707	89,506	18,450	0.59	0.17	0.12	0.04
0.65	3,512	3,463	0.50	596,415	9,195	92,969	14,987	0.62	0.14	0.09	0.03
0.70	2,644	3,002	0.53	599,059	6,551	95,971	11,985	0.65	0.11	0.06	0.03
0.75	1,948	2,648	0.58	601,007	4,603	98,619	9,337	0.67	0.09	0.04	0.02
0.80	1,474	2,290	0.61	602,481	3,129	100,909	7,047	0.69	0.07	0.03	0.01
0.85	1,115	1,959	0.64	603,596	2,014	102,868	5,088	0.72	0.05	0.02	0.01
0.90	776	1,738	0.69	604,372	1,238	104,606	3,350	0.73	0.03	0.01	0.01
0.95	564	1,334	0.70	604,936	674	105,940	2,016	0.75	0.02	0.01	0.00
1.00	674	2,016	0.75	605,610	0	107,956	0	nan	0.00	0.00	0.00

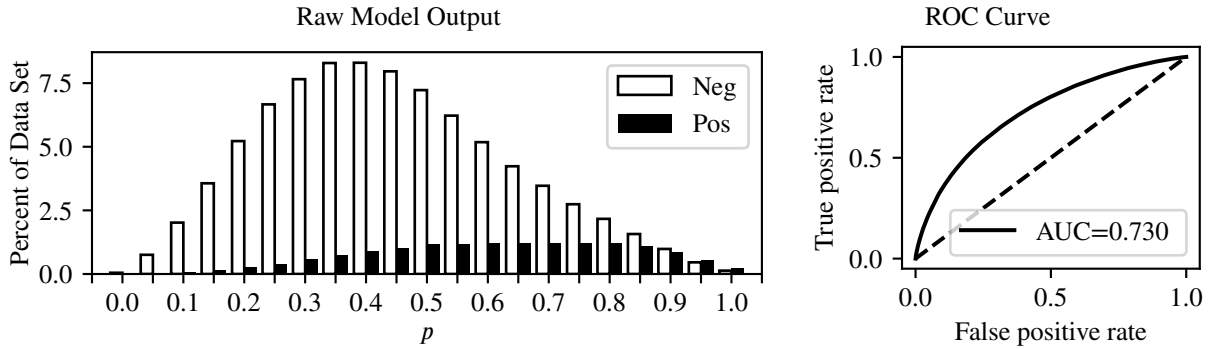
KBFC\_5\_Fold\_alpha\_0\_5\_gamma\_0\_0\_Hard\_Test\_Transformed\_95



	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
p											
0.00	15,141	125	0.01	15,141	590,469	125	107,831	0.15	1.00	5.47	0.98
0.05	151,124	4,545	0.03	166,265	439,345	4,670	103,286	0.19	0.96	4.07	0.76
0.10	120,766	8,621	0.07	287,031	318,579	13,291	94,665	0.23	0.88	2.95	0.58
0.15	86,646	10,066	0.10	373,677	231,933	23,357	84,599	0.27	0.78	2.15	0.44
0.20	61,706	10,135	0.14	435,383	170,227	33,492	74,464	0.30	0.69	1.58	0.34
0.25	44,710	9,645	0.18	480,093	125,517	43,137	64,819	0.34	0.60	1.16	0.27
0.30	32,403	8,684	0.21	512,496	93,114	51,821	56,135	0.38	0.52	0.86	0.21
0.35	23,596	7,768	0.25	536,092	69,518	59,589	48,367	0.41	0.45	0.64	0.17
0.40	17,390	6,723	0.28	553,482	52,128	66,312	41,644	0.44	0.39	0.48	0.13
0.45	12,994	5,890	0.31	566,476	39,134	72,202	35,754	0.48	0.33	0.36	0.10
0.50	9,589	5,136	0.35	576,065	29,545	77,338	30,618	0.51	0.28	0.27	0.08
0.55	7,254	4,608	0.39	583,319	22,291	81,946	26,010	0.54	0.24	0.21	0.07
0.60	5,497	4,098	0.43	588,816	16,794	86,044	21,912	0.57	0.20	0.16	0.05
0.65	4,189	3,546	0.46	593,005	12,605	89,590	18,366	0.59	0.17	0.12	0.04
0.70	3,249	3,195	0.50	596,254	9,356	92,785	15,171	0.62	0.14	0.09	0.03
0.75	2,497	2,800	0.53	598,751	6,859	95,585	12,371	0.64	0.11	0.06	0.03
0.80	1,862	2,478	0.57	600,613	4,997	98,063	9,893	0.66	0.09	0.05	0.02
0.85	1,498	2,199	0.59	602,111	3,499	100,262	7,694	0.69	0.07	0.03	0.02
0.90	1,115	1,898	0.63	603,226	2,384	102,160	5,796	0.71	0.05	0.02	0.01
0.95	845	1,690	0.67	604,071	1,539	103,850	4,106	0.73	0.04	0.01	0.01
1.00	1,539	4,106	0.73	605,610	0	107,956	0	nan	0.00	0.00	0.00

### 16.3. Medium Features

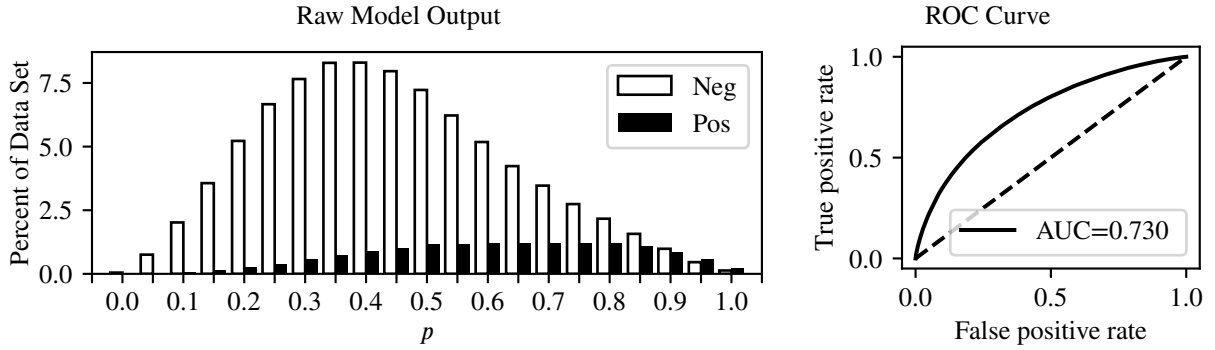
BRFC\_5\_Fold\_alpha\_0\_5\_Medium\_Test



$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	348	4	0.01	348	605,262	4	107,952	0.15	1.00	5.61	1.00
0.05	5,386	126	0.02	5,734	599,876	130	107,826	0.15	1.00	5.56	0.99
0.10	14,413	448	0.03	20,147	585,463	578	107,378	0.15	0.99	5.42	0.97
0.15	25,430	973	0.04	45,577	560,033	1,551	106,405	0.16	0.99	5.19	0.93
0.20	37,268	1,713	0.04	82,845	522,765	3,264	104,692	0.17	0.97	4.84	0.88
0.25	47,559	2,727	0.05	130,404	475,206	5,991	101,965	0.18	0.94	4.40	0.81
0.30	54,624	3,947	0.07	185,028	420,582	9,938	98,018	0.19	0.91	3.90	0.73
0.35	59,158	5,103	0.08	244,186	361,424	15,041	92,915	0.20	0.86	3.35	0.64
0.40	59,230	6,315	0.10	303,416	302,194	21,356	86,600	0.22	0.80	2.80	0.54
0.45	56,822	7,278	0.11	360,238	245,372	28,634	79,322	0.24	0.73	2.27	0.46
0.50	51,561	8,330	0.14	411,799	193,811	36,964	70,992	0.27	0.66	1.80	0.37
0.55	44,408	8,371	0.16	456,207	149,403	45,335	62,621	0.30	0.58	1.38	0.30
0.60	36,966	8,579	0.19	493,173	112,437	53,914	54,042	0.32	0.50	1.04	0.23
0.65	30,209	8,655	0.22	523,382	82,228	62,569	45,387	0.36	0.42	0.76	0.18
0.70	24,739	8,685	0.26	548,121	57,489	71,254	36,702	0.39	0.34	0.53	0.13
0.75	19,564	8,647	0.31	567,685	37,925	79,901	28,055	0.43	0.26	0.35	0.09
0.80	15,464	8,588	0.36	583,149	22,461	88,489	19,467	0.46	0.18	0.21	0.06
0.85	11,212	7,715	0.41	594,361	11,249	96,204	11,752	0.51	0.11	0.10	0.03
0.90	7,030	6,154	0.47	601,391	4,219	102,358	5,598	0.57	0.05	0.04	0.01
0.95	3,275	3,932	0.55	604,666	944	106,290	1,666	0.64	0.02	0.01	0.00
1.00	944	1,666	0.64	605,610	0	107,956	0	nan	0.00	0.00	0.00

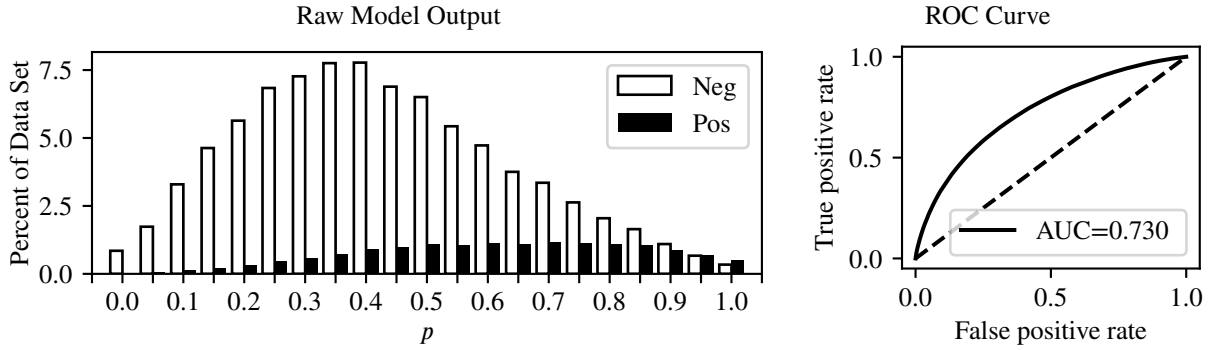


BRFC\_5\_Fold\_alpha\_0\_5\_Medium\_Test\_Transformed\_100



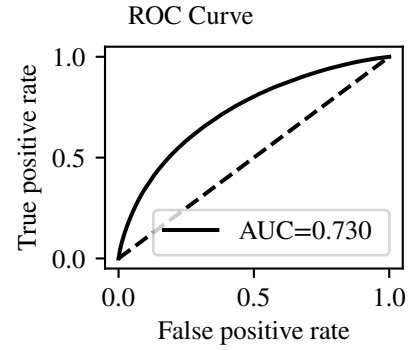
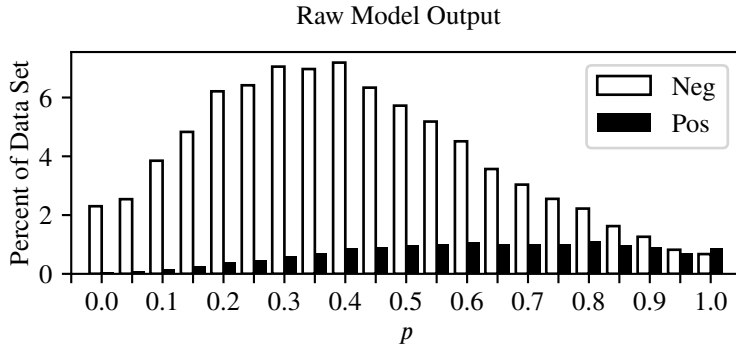
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	348	4	0.01	348	605,262	4	107,952	0.15	1.00	5.61	1.00
0.05	5,386	126	0.02	5,734	599,876	130	107,826	0.15	1.00	5.56	0.99
0.10	14,413	448	0.03	20,147	585,463	578	107,378	0.15	0.99	5.42	0.97
0.15	25,430	973	0.04	45,577	560,033	1,551	106,405	0.16	0.99	5.19	0.93
0.20	37,268	1,713	0.04	82,845	522,765	3,264	104,692	0.17	0.97	4.84	0.88
0.25	47,559	2,727	0.05	130,404	475,206	5,991	101,965	0.18	0.94	4.40	0.81
0.30	54,624	3,947	0.07	185,028	420,582	9,938	98,018	0.19	0.91	3.90	0.73
0.35	59,158	5,103	0.08	244,186	361,424	15,041	92,915	0.20	0.86	3.35	0.64
0.40	59,230	6,315	0.10	303,416	302,194	21,356	86,600	0.22	0.80	2.80	0.54
0.45	56,822	7,278	0.11	360,238	245,372	28,634	79,322	0.24	0.73	2.27	0.46
0.50	51,561	8,330	0.14	411,799	193,811	36,964	70,992	0.27	0.66	1.80	0.37
0.55	44,408	8,371	0.16	456,207	149,403	45,335	62,621	0.30	0.58	1.38	0.30
0.60	36,966	8,579	0.19	493,173	112,437	53,914	54,042	0.32	0.50	1.04	0.23
0.65	30,209	8,655	0.22	523,382	82,228	62,569	45,387	0.36	0.42	0.76	0.18
0.70	24,739	8,685	0.26	548,121	57,489	71,254	36,702	0.39	0.34	0.53	0.13
0.75	19,564	8,647	0.31	567,685	37,925	79,901	28,055	0.43	0.26	0.35	0.09
0.80	15,464	8,588	0.36	583,149	22,461	88,489	19,467	0.46	0.18	0.21	0.06
0.85	11,212	7,715	0.41	594,361	11,249	96,204	11,752	0.51	0.11	0.10	0.03
0.90	7,030	6,154	0.47	601,391	4,219	102,358	5,598	0.57	0.05	0.04	0.01
0.95	3,275	3,932	0.55	604,666	944	106,290	1,666	0.64	0.02	0.01	0.00
1.00	944	1,666	0.64	605,610	0	107,956	0	nan	0.00	0.00	0.00

BRFC\_5\_Fold\_alpha\_0\_5\_Medium\_Test\_Transformed\_98



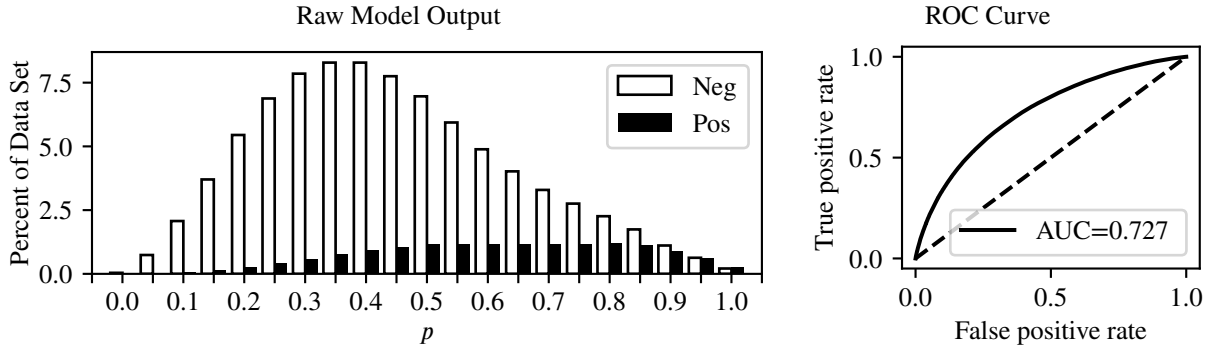
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	6,061	135	0.02	6,061	599,549	135	107,821	0.15	1.00	5.55	0.99
0.05	12,379	398	0.03	18,440	587,170	533	107,423	0.15	1.00	5.44	0.97
0.10	23,504	871	0.04	41,944	563,666	1,404	106,552	0.16	0.99	5.22	0.94
0.15	33,039	1,449	0.04	74,983	530,627	2,853	105,103	0.17	0.97	4.92	0.89
0.20	40,228	2,246	0.05	115,211	490,399	5,099	102,857	0.17	0.95	4.54	0.83
0.25	48,806	3,277	0.06	164,017	441,593	8,376	99,580	0.18	0.92	4.09	0.76
0.30	51,878	4,165	0.07	215,895	389,715	12,541	95,415	0.20	0.88	3.61	0.68
0.35	55,333	5,223	0.09	271,228	334,382	17,764	90,192	0.21	0.84	3.10	0.60
0.40	55,475	6,428	0.10	326,703	278,907	24,192	83,764	0.23	0.78	2.58	0.51
0.45	49,159	6,865	0.12	375,862	229,748	31,057	76,899	0.25	0.71	2.13	0.43
0.50	46,427	7,703	0.14	422,289	183,321	38,760	69,196	0.27	0.64	1.70	0.35
0.55	38,754	7,590	0.16	461,043	144,567	46,350	61,606	0.30	0.57	1.34	0.29
0.60	33,727	7,943	0.19	494,770	110,840	54,293	53,663	0.33	0.50	1.03	0.23
0.65	26,786	7,686	0.22	521,556	84,054	61,979	45,977	0.35	0.43	0.78	0.18
0.70	23,919	8,216	0.26	545,475	60,135	70,195	37,761	0.39	0.35	0.56	0.14
0.75	18,765	7,998	0.30	564,240	41,370	78,193	29,763	0.42	0.28	0.38	0.10
0.80	14,605	7,654	0.34	578,845	26,765	85,847	22,109	0.45	0.20	0.25	0.07
0.85	11,741	7,474	0.39	590,586	15,024	93,321	14,635	0.49	0.14	0.14	0.04
0.90	7,827	6,130	0.44	598,413	7,197	99,451	8,505	0.54	0.08	0.07	0.02
0.95	4,769	4,899	0.51	603,182	2,428	104,350	3,606	0.60	0.03	0.02	0.01
1.00	2,428	3,606	0.60	605,610	0	107,956	0	nan	0.00	0.00	0.00

BRFC\_5\_Fold\_alpha\_0\_5\_Medium\_Test\_Transformed\_95



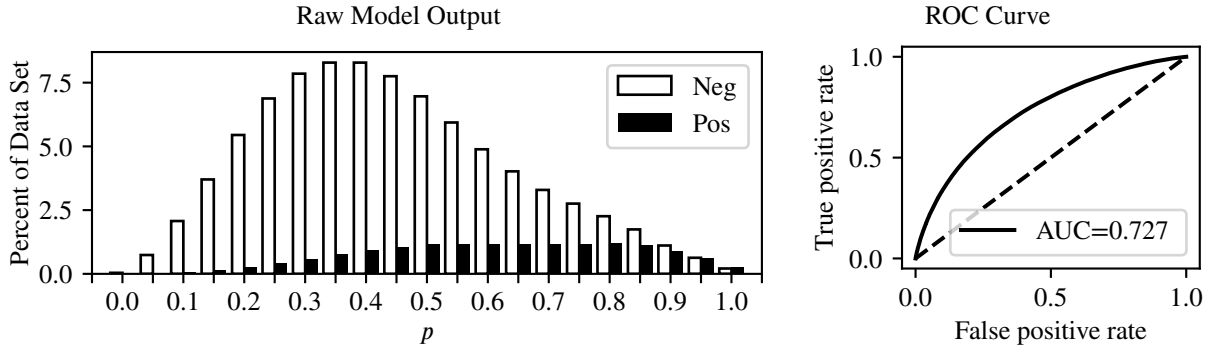
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	16,420	464	0.03	16,420	589,190	464	107,492	0.15	1.00	5.46	0.98
0.05	18,131	636	0.03	34,551	571,059	1,100	106,856	0.16	0.99	5.29	0.95
0.10	27,471	1,157	0.04	62,022	543,588	2,257	105,699	0.16	0.98	5.04	0.91
0.15	34,466	1,758	0.05	96,488	509,122	4,015	103,941	0.17	0.96	4.72	0.86
0.20	44,322	2,700	0.06	140,810	464,800	6,715	101,241	0.18	0.94	4.31	0.79
0.25	45,790	3,351	0.07	186,600	419,010	10,066	97,890	0.19	0.91	3.88	0.72
0.30	50,319	4,339	0.08	236,919	368,691	14,405	93,551	0.20	0.87	3.42	0.65
0.35	49,733	5,000	0.09	286,652	318,958	19,405	88,551	0.22	0.82	2.95	0.57
0.40	51,296	6,232	0.11	337,948	267,662	25,637	82,319	0.24	0.76	2.48	0.49
0.45	45,215	6,550	0.13	383,163	222,447	32,187	75,769	0.25	0.70	2.06	0.42
0.50	40,845	6,877	0.14	424,008	181,602	39,064	68,892	0.28	0.64	1.68	0.35
0.55	36,980	7,273	0.16	460,988	144,622	46,337	61,619	0.30	0.57	1.34	0.29
0.60	32,185	7,577	0.19	493,173	112,437	53,914	54,042	0.32	0.50	1.04	0.23
0.65	25,457	7,162	0.22	518,630	86,980	61,076	46,880	0.35	0.43	0.81	0.19
0.70	21,668	7,204	0.25	540,298	65,312	68,280	39,676	0.38	0.37	0.60	0.15
0.75	18,210	7,260	0.29	558,508	47,102	75,540	32,416	0.41	0.30	0.44	0.11
0.80	15,849	7,844	0.33	574,357	31,253	83,384	24,572	0.44	0.23	0.29	0.08
0.85	11,595	6,811	0.37	585,952	19,658	90,195	17,761	0.47	0.16	0.18	0.05
0.90	9,004	6,457	0.42	594,956	10,654	96,652	11,304	0.51	0.10	0.10	0.03
0.95	5,853	5,004	0.46	600,809	4,801	101,656	6,300	0.57	0.06	0.04	0.02
1.00	4,801	6,300	0.57	605,610	0	107,956	0	nan	0.00	0.00	0.00

BRFC\_5\_Fold\_alpha\_balanced\_Medium\_Test



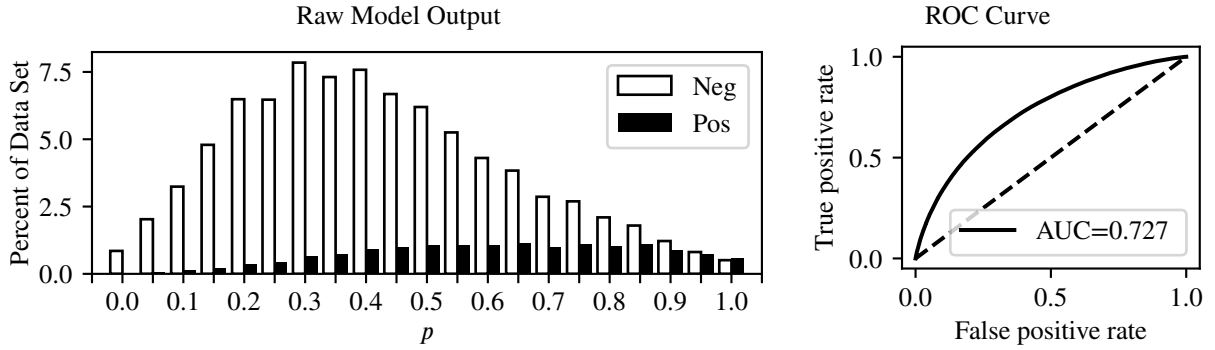
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	288	2	0.01	288	605,322	2	107,954	0.15	1.00	5.61	1.00
0.05	5,275	113	0.02	5,563	600,047	115	107,841	0.15	1.00	5.56	0.99
0.10	14,784	420	0.03	20,347	585,263	535	107,421	0.16	1.00	5.42	0.97
0.15	26,422	943	0.03	46,769	558,841	1,478	106,478	0.16	0.99	5.18	0.93
0.20	38,868	1,797	0.04	85,637	519,973	3,275	104,681	0.17	0.97	4.82	0.88
0.25	49,086	2,886	0.06	134,723	470,887	6,161	101,795	0.18	0.94	4.36	0.80
0.30	56,034	4,030	0.07	190,757	414,853	10,191	97,765	0.19	0.91	3.84	0.72
0.35	59,129	5,369	0.08	249,886	355,724	15,560	92,396	0.21	0.86	3.30	0.63
0.40	59,130	6,453	0.10	309,016	296,594	22,013	85,943	0.22	0.80	2.75	0.54
0.45	55,318	7,338	0.12	364,334	241,276	29,351	78,605	0.25	0.73	2.23	0.45
0.50	49,690	8,295	0.14	414,024	191,586	37,646	70,310	0.27	0.65	1.77	0.37
0.55	42,368	8,315	0.16	456,392	149,218	45,961	61,995	0.29	0.57	1.38	0.30
0.60	34,865	8,350	0.19	491,257	114,353	54,311	53,645	0.32	0.50	1.06	0.24
0.65	28,689	8,276	0.22	519,946	85,664	62,587	45,369	0.35	0.42	0.79	0.18
0.70	23,494	8,205	0.26	543,440	62,170	70,792	37,164	0.37	0.34	0.58	0.14
0.75	19,662	8,293	0.30	563,102	42,508	79,085	28,871	0.40	0.27	0.39	0.10
0.80	16,132	8,436	0.34	579,234	26,376	87,521	20,435	0.44	0.19	0.24	0.07
0.85	12,441	7,904	0.39	591,675	13,935	95,425	12,531	0.47	0.12	0.13	0.04
0.90	7,935	6,434	0.45	599,610	6,000	101,859	6,097	0.50	0.06	0.06	0.02
0.95	4,501	4,242	0.49	604,111	1,499	106,101	1,855	0.55	0.02	0.01	0.00
1.00	1,499	1,855	0.55	605,610	0	107,956	0	nan	0.00	0.00	0.00

BRFC\_5\_Fold\_alpha\_balanced\_Medium\_Test\_Transformed\_100



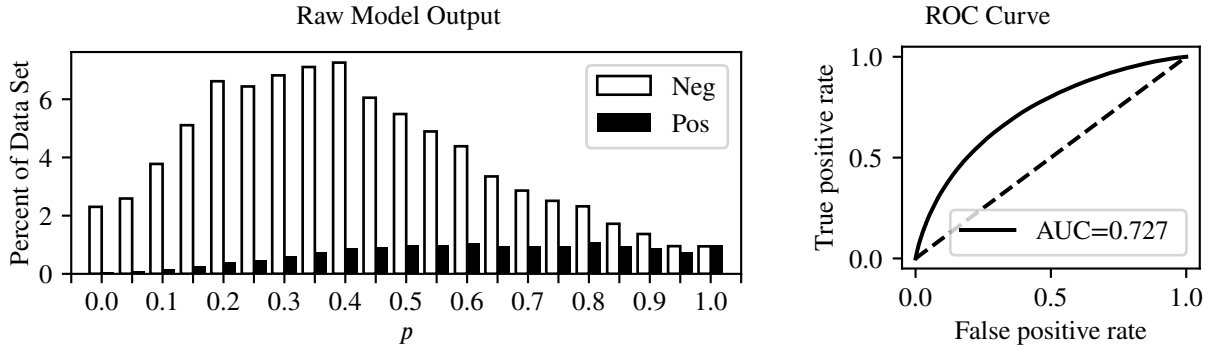
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	288	2	0.01	288	605,322	2	107,954	0.15	1.00	5.61	1.00
0.05	5,275	113	0.02	5,563	600,047	115	107,841	0.15	1.00	5.56	0.99
0.10	14,784	420	0.03	20,347	585,263	535	107,421	0.16	1.00	5.42	0.97
0.15	26,422	943	0.03	46,769	558,841	1,478	106,478	0.16	0.99	5.18	0.93
0.20	38,868	1,797	0.04	85,637	519,973	3,275	104,681	0.17	0.97	4.82	0.88
0.25	49,086	2,886	0.06	134,723	470,887	6,161	101,795	0.18	0.94	4.36	0.80
0.30	56,034	4,030	0.07	190,757	414,853	10,191	97,765	0.19	0.91	3.84	0.72
0.35	59,129	5,369	0.08	249,886	355,724	15,560	92,396	0.21	0.86	3.30	0.63
0.40	59,130	6,453	0.10	309,016	296,594	22,013	85,943	0.22	0.80	2.75	0.54
0.45	55,318	7,338	0.12	364,334	241,276	29,351	78,605	0.25	0.73	2.23	0.45
0.50	49,690	8,295	0.14	414,024	191,586	37,646	70,310	0.27	0.65	1.77	0.37
0.55	42,368	8,315	0.16	456,392	149,218	45,961	61,995	0.29	0.57	1.38	0.30
0.60	34,865	8,350	0.19	491,257	114,353	54,311	53,645	0.32	0.50	1.06	0.24
0.65	28,689	8,276	0.22	519,946	85,664	62,587	45,369	0.35	0.42	0.79	0.18
0.70	23,494	8,205	0.26	543,440	62,170	70,792	37,164	0.37	0.34	0.58	0.14
0.75	19,662	8,293	0.30	563,102	42,508	79,085	28,871	0.40	0.27	0.39	0.10
0.80	16,132	8,436	0.34	579,234	26,376	87,521	20,435	0.44	0.19	0.24	0.07
0.85	12,441	7,904	0.39	591,675	13,935	95,425	12,531	0.47	0.12	0.13	0.04
0.90	7,935	6,434	0.45	599,610	6,000	101,859	6,097	0.50	0.06	0.06	0.02
0.95	4,501	4,242	0.49	604,111	1,499	106,101	1,855	0.55	0.02	0.01	0.00
1.00	1,499	1,855	0.55	605,610	0	107,956	0	nan	0.00	0.00	0.00

BRFC\_5\_Fold\_alpha\_balanced\_Medium\_Test\_Transformed\_98



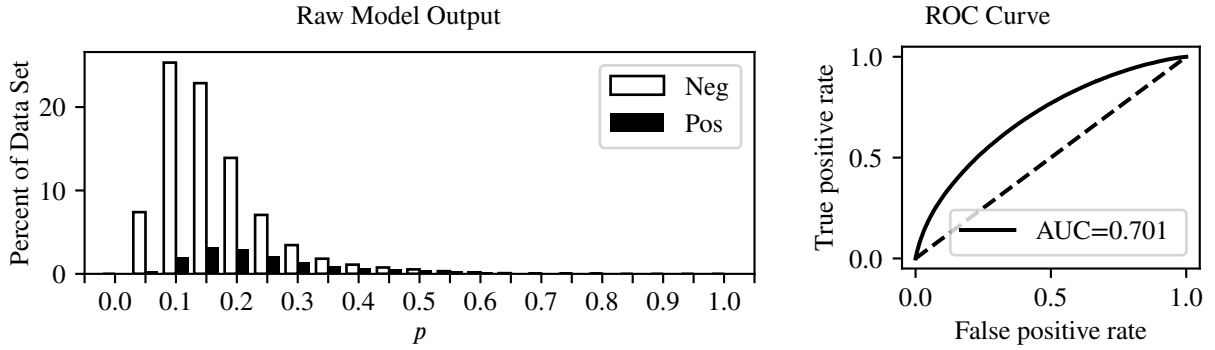
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	6,081	129	0.02	6,081	599,529	129	107,827	0.15	1.00	5.55	0.99
0.05	14,480	414	0.03	20,561	585,049	543	107,413	0.16	0.99	5.42	0.97
0.10	23,120	826	0.03	43,681	561,929	1,369	106,587	0.16	0.99	5.21	0.94
0.15	34,197	1,525	0.04	77,878	527,732	2,894	105,062	0.17	0.97	4.89	0.89
0.20	46,292	2,586	0.05	124,170	481,440	5,480	102,476	0.18	0.95	4.46	0.82
0.25	46,173	3,175	0.06	170,343	435,267	8,655	99,301	0.19	0.92	4.03	0.75
0.30	55,996	4,639	0.08	226,339	379,271	13,294	94,662	0.20	0.88	3.51	0.66
0.35	52,168	5,244	0.09	278,507	327,103	18,538	89,418	0.21	0.83	3.03	0.58
0.40	54,090	6,394	0.11	332,597	273,013	24,932	83,024	0.23	0.77	2.53	0.50
0.45	47,661	6,943	0.13	380,258	225,352	31,875	76,081	0.25	0.70	2.09	0.42
0.50	44,227	7,670	0.15	424,485	181,125	39,545	68,411	0.27	0.63	1.68	0.35
0.55	37,488	7,667	0.17	461,973	143,637	47,212	60,744	0.30	0.56	1.33	0.29
0.60	30,718	7,462	0.20	492,691	112,919	54,674	53,282	0.32	0.49	1.05	0.23
0.65	27,371	7,955	0.23	520,062	85,548	62,629	45,327	0.35	0.42	0.79	0.18
0.70	20,431	6,959	0.25	540,493	65,117	69,588	38,368	0.37	0.36	0.60	0.15
0.75	19,221	7,922	0.29	559,714	45,896	77,510	30,446	0.40	0.28	0.43	0.11
0.80	14,971	7,218	0.33	574,685	30,925	84,728	23,228	0.43	0.22	0.29	0.08
0.85	12,806	7,809	0.38	587,491	18,119	92,537	15,419	0.46	0.14	0.17	0.05
0.90	8,703	6,180	0.42	596,194	9,416	98,717	9,239	0.50	0.09	0.09	0.03
0.95	5,788	5,148	0.47	601,982	3,628	103,865	4,091	0.53	0.04	0.03	0.01
1.00	3,628	4,091	0.53	605,610	0	107,956	0	nan	0.00	0.00	0.00

BRFC\_5\_Fold\_alpha\_balanced\_Medium\_Test\_Transformed\_95



$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	16,433	414	0.02	16,433	589,177	414	107,542	0.15	1.00	5.46	0.98
0.05	18,474	612	0.03	34,907	570,703	1,026	106,930	0.16	0.99	5.29	0.95
0.10	26,951	1,101	0.04	61,858	543,752	2,127	105,829	0.16	0.98	5.04	0.91
0.15	36,449	1,900	0.05	98,307	507,303	4,027	103,929	0.17	0.96	4.70	0.86
0.20	47,229	2,875	0.06	145,536	460,074	6,902	101,054	0.18	0.94	4.26	0.79
0.25	45,948	3,365	0.07	191,484	414,126	10,267	97,689	0.19	0.90	3.84	0.72
0.30	48,668	4,402	0.08	240,152	365,458	14,669	93,287	0.20	0.86	3.39	0.64
0.35	50,720	5,277	0.09	290,872	314,738	19,946	88,010	0.22	0.82	2.92	0.56
0.40	51,800	6,350	0.11	342,672	262,938	26,296	81,660	0.24	0.76	2.44	0.48
0.45	43,190	6,462	0.13	385,862	219,748	32,758	75,198	0.25	0.70	2.04	0.41
0.50	39,191	6,883	0.15	425,053	180,557	39,641	68,315	0.27	0.63	1.67	0.35
0.55	34,918	7,101	0.17	459,971	145,639	46,742	61,214	0.30	0.57	1.35	0.29
0.60	31,286	7,569	0.19	491,257	114,353	54,311	53,645	0.32	0.50	1.06	0.24
0.65	23,889	6,755	0.22	515,146	90,464	61,066	46,890	0.34	0.43	0.84	0.19
0.70	20,418	6,792	0.25	535,564	70,046	67,858	40,098	0.36	0.37	0.65	0.15
0.75	17,905	6,814	0.28	553,469	52,141	74,672	33,284	0.39	0.31	0.48	0.12
0.80	16,555	7,789	0.32	570,024	35,586	82,461	25,495	0.42	0.24	0.33	0.09
0.85	12,277	6,778	0.36	582,301	23,309	89,239	18,717	0.45	0.17	0.22	0.06
0.90	9,774	6,375	0.39	592,075	13,535	95,614	12,342	0.48	0.11	0.13	0.04
0.95	6,791	5,377	0.44	598,866	6,744	100,991	6,965	0.51	0.06	0.06	0.02
1.00	6,744	6,965	0.51	605,610	0	107,956	0	nan	0.00	0.00	0.00

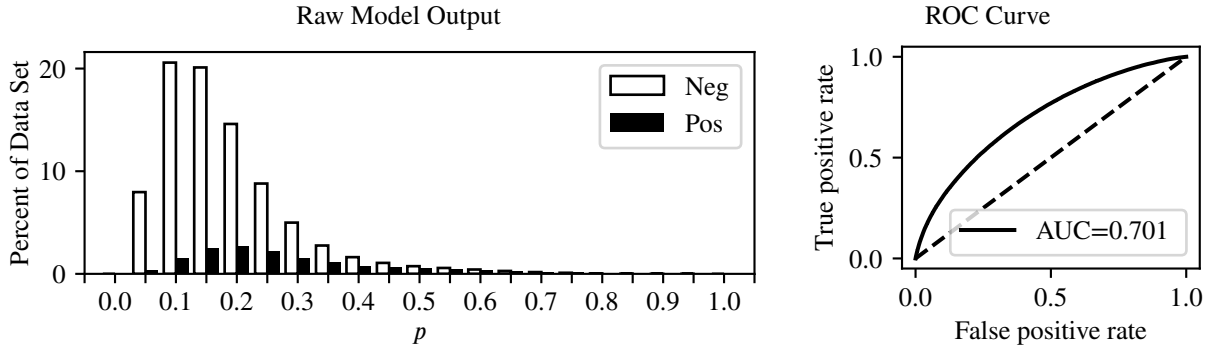
LogReg\_5\_Fold\_alpha\_0\_5\_Medium\_Test



	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
$p$											
0.00	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.05	52,811	2,049	0.04	52,811	552,799	2,049	105,907	0.16	0.98	5.12	0.92
0.10	180,779	14,384	0.07	233,590	372,020	16,433	91,523	0.20	0.85	3.45	0.65
0.15	163,197	23,099	0.12	396,787	208,823	39,532	68,424	0.25	0.63	1.93	0.39
0.20	99,231	21,227	0.18	496,018	109,592	60,759	47,197	0.30	0.44	1.02	0.22
0.25	50,431	14,861	0.23	546,449	59,161	75,620	32,336	0.35	0.30	0.55	0.13
0.30	24,611	9,477	0.28	571,060	34,550	85,097	22,859	0.40	0.21	0.32	0.08
0.35	12,961	6,357	0.33	584,021	21,589	91,454	16,502	0.43	0.15	0.20	0.05
0.40	7,880	4,846	0.38	591,901	13,709	96,300	11,656	0.46	0.11	0.13	0.04
0.45	5,461	3,865	0.41	597,362	8,248	100,165	7,791	0.49	0.07	0.08	0.02
0.50	3,828	3,217	0.46	601,190	4,420	103,382	4,574	0.51	0.04	0.04	0.01
0.55	2,310	2,254	0.49	603,500	2,110	105,636	2,320	0.52	0.02	0.02	0.01
0.60	1,304	1,348	0.51	604,804	806	106,984	972	0.55	0.01	0.01	0.00
0.65	591	680	0.54	605,395	215	107,664	292	0.58	0.00	0.00	0.00
0.70	166	225	0.58	605,561	49	107,889	67	0.58	0.00	0.00	0.00
0.75	46	59	0.56	605,607	3	107,948	8	0.73	0.00	0.00	0.00
0.80	3	7	0.70	605,610	0	107,955	1	1.00	0.00	0.00	0.00
0.85	0	1	1.00	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.90	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.95	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
1.00	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00

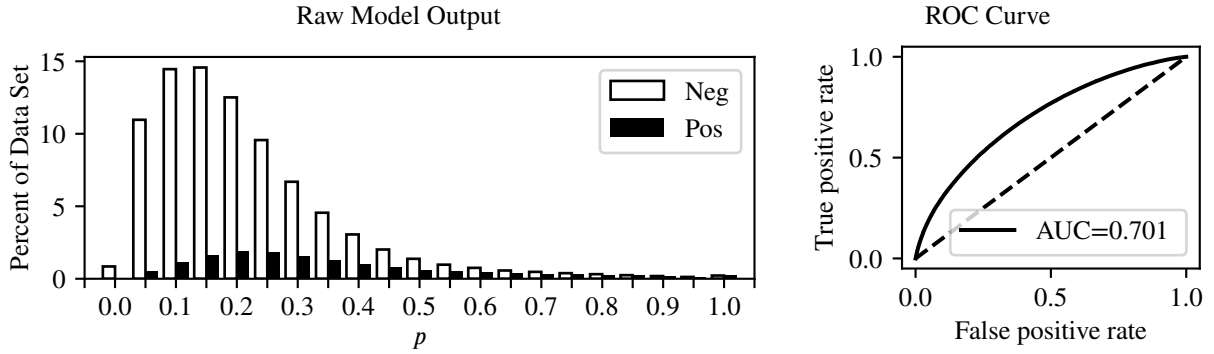


LogReg\_5\_Fold\_alpha\_0\_5\_Medium\_Test\_Transformed\_100



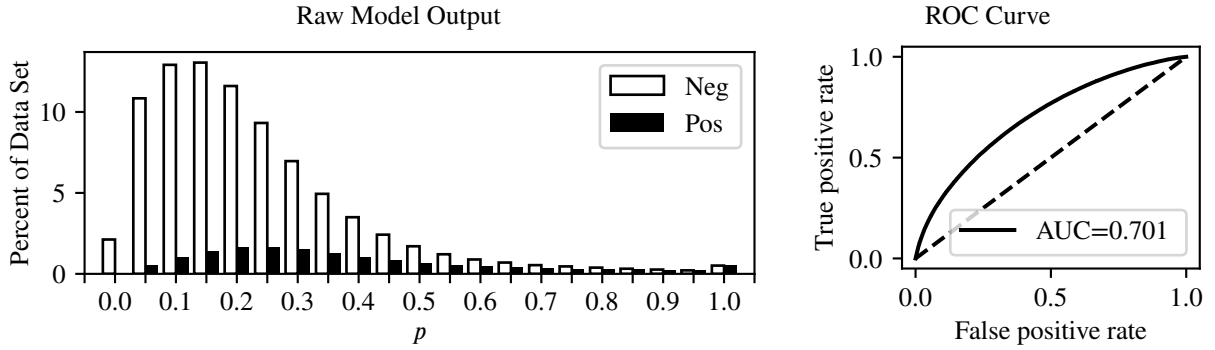
	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
p											
0.00	1	0	0.00	1	605,609	0	107,956	0.15	1.00	5.61	1.00
0.05	56,826	2,244	0.04	56,827	548,783	2,244	105,712	0.16	0.98	5.08	0.92
0.10	146,862	11,058	0.07	203,689	401,921	13,302	94,654	0.19	0.88	3.72	0.70
0.15	143,489	17,982	0.11	347,178	258,432	31,284	76,672	0.23	0.71	2.39	0.47
0.20	104,202	18,972	0.15	451,380	154,230	50,256	57,700	0.27	0.53	1.43	0.30
0.25	62,784	15,380	0.20	514,164	91,446	65,636	42,320	0.32	0.39	0.85	0.19
0.30	35,624	11,112	0.24	549,788	55,822	76,748	31,208	0.36	0.29	0.52	0.12
0.35	19,701	7,679	0.28	569,489	36,121	84,427	23,529	0.39	0.22	0.33	0.08
0.40	11,606	5,536	0.32	581,095	24,515	89,963	17,993	0.42	0.17	0.23	0.06
0.45	7,612	4,257	0.36	588,707	16,903	94,220	13,736	0.45	0.13	0.16	0.04
0.50	5,332	3,527	0.40	594,039	11,571	97,747	10,209	0.47	0.09	0.11	0.03
0.55	4,095	3,033	0.43	598,134	7,476	100,780	7,176	0.49	0.07	0.07	0.02
0.60	3,020	2,563	0.46	601,154	4,456	103,343	4,613	0.51	0.04	0.04	0.01
0.65	2,020	1,966	0.49	603,174	2,436	105,309	2,647	0.52	0.02	0.02	0.01
0.70	1,236	1,203	0.49	604,410	1,200	106,512	1,444	0.55	0.01	0.01	0.00
0.75	744	845	0.53	605,154	456	107,357	599	0.57	0.01	0.00	0.00
0.80	301	390	0.56	605,455	155	107,747	209	0.57	0.00	0.00	0.00
0.85	117	151	0.56	605,572	38	107,898	58	0.60	0.00	0.00	0.00
0.90	35	49	0.58	605,607	3	107,947	9	0.75	0.00	0.00	0.00
0.95	3	8	0.73	605,610	0	107,955	1	1.00	0.00	0.00	0.00
1.00	0	1	1.00	605,610	0	107,956	0	nan	0.00	0.00	0.00

LogReg\_5\_Fold\_alpha\_0\_5\_Medium\_Test\_Transformed\_98



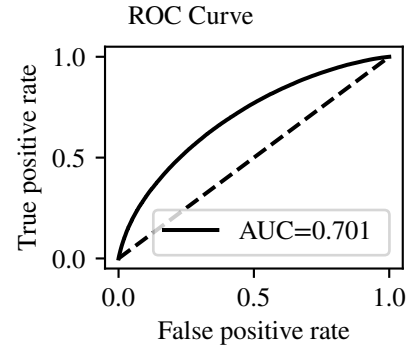
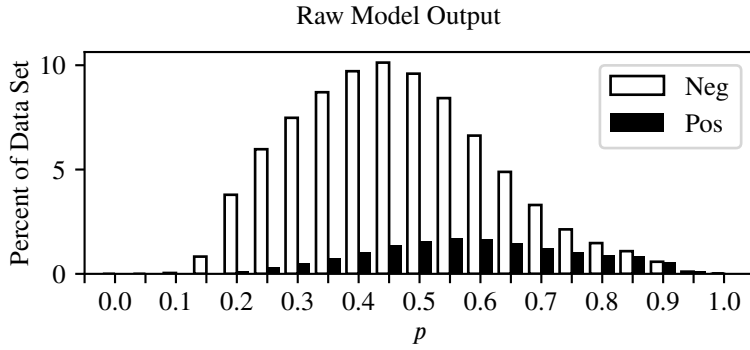
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	6,057	156	0.03	6,057	599,553	156	107,800	0.15	1.00	5.55	0.99
0.05	78,242	3,634	0.04	84,299	521,311	3,790	104,166	0.17	0.96	4.83	0.88
0.10	103,170	7,996	0.07	187,469	418,141	11,786	96,170	0.19	0.89	3.87	0.72
0.15	103,976	11,578	0.10	291,445	314,165	23,364	84,592	0.21	0.78	2.91	0.56
0.20	89,260	13,350	0.13	380,705	224,905	36,714	71,242	0.24	0.66	2.08	0.42
0.25	68,266	13,029	0.16	448,971	156,639	49,743	58,213	0.27	0.54	1.45	0.30
0.30	47,738	11,167	0.19	496,709	108,901	60,910	47,046	0.30	0.44	1.01	0.22
0.35	32,498	9,120	0.22	529,207	76,403	70,030	37,926	0.33	0.35	0.71	0.16
0.40	21,815	7,182	0.25	551,022	54,588	77,212	30,744	0.36	0.28	0.51	0.12
0.45	14,399	5,457	0.27	565,421	40,189	82,669	25,287	0.39	0.23	0.37	0.09
0.50	9,824	4,364	0.31	575,245	30,365	87,033	20,923	0.41	0.19	0.28	0.07
0.55	6,933	3,507	0.34	582,178	23,432	90,540	17,416	0.43	0.16	0.22	0.06
0.60	5,368	2,959	0.36	587,546	18,064	93,499	14,457	0.44	0.13	0.17	0.05
0.65	4,070	2,609	0.39	591,616	13,994	96,108	11,848	0.46	0.11	0.13	0.04
0.70	3,393	2,324	0.41	595,009	10,601	98,432	9,524	0.47	0.09	0.10	0.03
0.75	2,753	2,057	0.43	597,762	7,848	100,489	7,467	0.49	0.07	0.07	0.02
0.80	2,256	1,852	0.45	600,018	5,592	102,341	5,615	0.50	0.05	0.05	0.02
0.85	1,773	1,623	0.48	601,791	3,819	103,964	3,992	0.51	0.04	0.04	0.01
0.90	1,335	1,313	0.50	603,126	2,484	105,277	2,679	0.52	0.02	0.02	0.01
0.95	895	896	0.50	604,021	1,589	106,173	1,783	0.53	0.02	0.01	0.00
1.00	1,589	1,783	0.53	605,610	0	107,956	0	nan	0.00	0.00	0.00

LogReg\_5\_Fold\_alpha\_0\_5\_Medium\_Test\_Transformed\_95



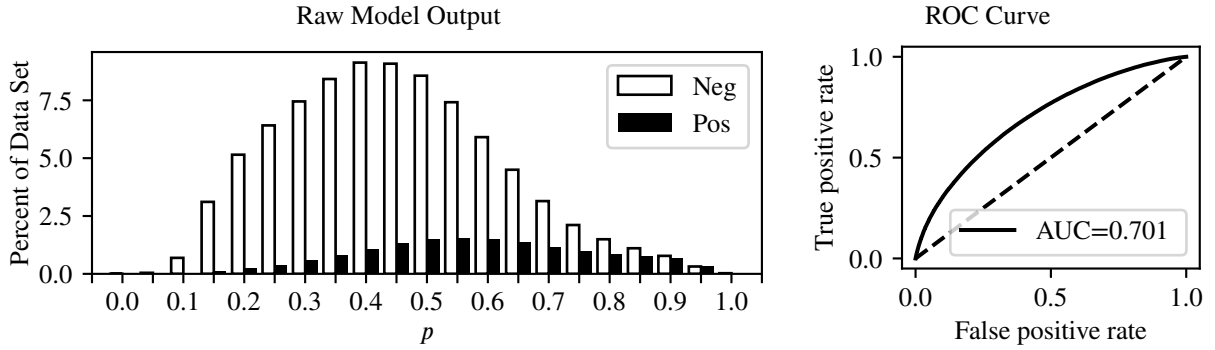
	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
p											
0.00	15,141	414	0.03	15,141	590,469	414	107,542	0.15	1.00	5.47	0.98
0.05	77,373	3,855	0.05	92,514	513,096	4,269	103,687	0.17	0.96	4.75	0.86
0.10	92,135	7,226	0.07	184,649	420,961	11,495	96,461	0.19	0.89	3.90	0.73
0.15	93,123	10,069	0.10	277,772	327,838	21,564	86,392	0.21	0.80	3.04	0.58
0.20	82,801	11,811	0.12	360,573	245,037	33,375	74,581	0.23	0.69	2.27	0.45
0.25	66,515	11,897	0.15	427,088	178,522	45,272	62,684	0.26	0.58	1.65	0.34
0.30	49,695	10,734	0.18	476,783	128,827	56,006	51,950	0.29	0.48	1.19	0.25
0.35	35,268	9,035	0.20	512,051	93,559	65,041	42,915	0.31	0.40	0.87	0.19
0.40	24,966	7,363	0.23	537,017	68,593	72,404	35,552	0.34	0.33	0.64	0.15
0.45	17,275	5,988	0.26	554,292	51,318	78,392	29,564	0.37	0.27	0.48	0.11
0.50	12,158	4,703	0.28	566,450	39,160	83,095	24,861	0.39	0.23	0.36	0.09
0.55	8,630	3,870	0.31	575,080	30,530	86,965	20,991	0.41	0.19	0.28	0.07
0.60	6,337	3,166	0.33	581,417	24,193	90,131	17,825	0.42	0.17	0.22	0.06
0.65	4,987	2,696	0.35	586,404	19,206	92,827	15,129	0.44	0.14	0.18	0.05
0.70	3,841	2,434	0.39	590,245	15,365	95,261	12,695	0.45	0.12	0.14	0.04
0.75	3,281	2,127	0.39	593,526	12,084	97,388	10,568	0.47	0.10	0.11	0.03
0.80	2,747	1,902	0.41	596,273	9,337	99,290	8,666	0.48	0.08	0.09	0.03
0.85	2,263	1,800	0.44	598,536	7,074	101,090	6,866	0.49	0.06	0.07	0.02
0.90	1,890	1,617	0.46	600,426	5,184	102,707	5,249	0.50	0.05	0.05	0.01
0.95	1,537	1,401	0.48	601,963	3,647	104,108	3,848	0.51	0.04	0.03	0.01
1.00	3,647	3,848	0.51	605,610	0	107,956	0	nan	0.00	0.00	0.00

LogReg\_5\_Fold\_alpha\_balanced\_Medium\_Test



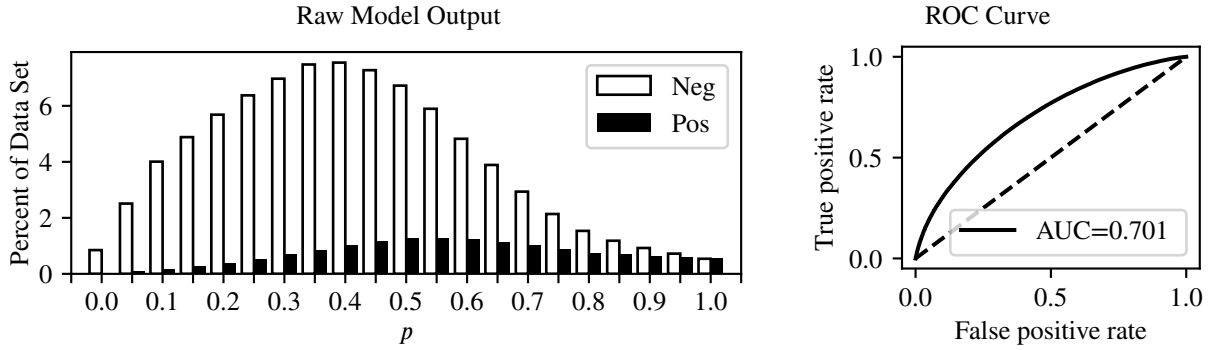
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.05	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.10	300	7	0.02	300	605,310	7	107,949	0.15	1.00	5.61	1.00
0.15	5,902	155	0.03	6,202	599,408	162	107,794	0.15	1.00	5.55	0.99
0.20	27,045	933	0.03	33,247	572,363	1,095	106,861	0.16	0.99	5.30	0.95
0.25	42,627	2,212	0.05	75,874	529,736	3,307	104,649	0.16	0.97	4.91	0.89
0.30	53,369	3,509	0.06	129,243	476,367	6,816	101,140	0.18	0.94	4.41	0.81
0.35	62,118	5,199	0.08	191,361	414,249	12,015	95,941	0.19	0.89	3.84	0.71
0.40	69,311	7,446	0.10	260,672	344,938	19,461	88,495	0.20	0.82	3.20	0.61
0.45	72,256	9,620	0.12	332,928	272,682	29,081	78,875	0.22	0.73	2.53	0.49
0.50	68,467	11,143	0.14	401,395	204,215	40,224	67,732	0.25	0.63	1.89	0.38
0.55	60,109	12,217	0.17	461,504	144,106	52,441	55,515	0.28	0.51	1.33	0.28
0.60	47,285	11,746	0.20	508,789	96,821	64,187	43,769	0.31	0.41	0.90	0.20
0.65	34,876	10,493	0.23	543,665	61,945	74,680	33,276	0.35	0.31	0.57	0.13
0.70	23,552	8,881	0.27	567,217	38,393	83,561	24,395	0.39	0.23	0.36	0.09
0.75	15,214	7,202	0.32	582,431	23,179	90,763	17,193	0.43	0.16	0.21	0.06
0.80	10,524	6,389	0.38	592,955	12,655	97,152	10,804	0.46	0.10	0.12	0.03
0.85	7,760	5,880	0.43	600,715	4,895	103,032	4,924	0.50	0.05	0.05	0.01
0.90	4,139	4,035	0.49	604,854	756	107,067	889	0.54	0.01	0.01	0.00
0.95	754	885	0.54	605,608	2	107,952	4	0.67	0.00	0.00	0.00
1.00	2	4	0.67	605,610	0	107,956	0	nan	0.00	0.00	0.00

LogReg\_5\_Fold\_alpha\_balanced\_Medium\_Test\_Transformed\_100



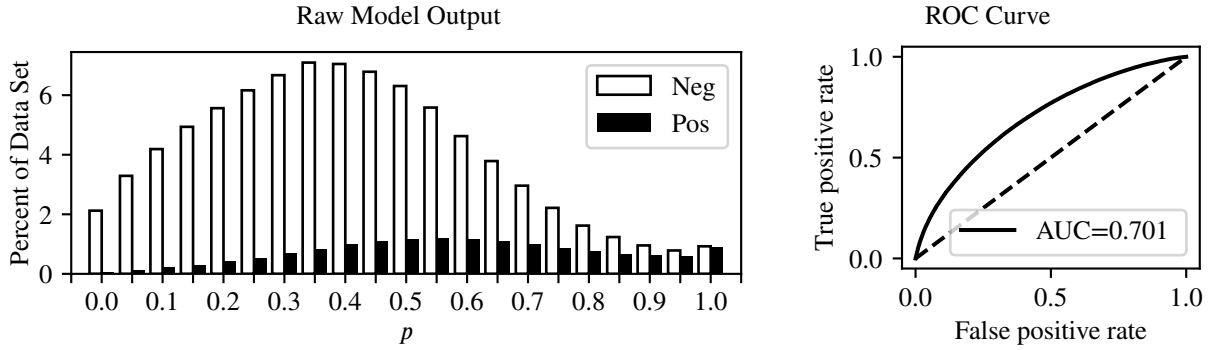
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	1	0	0.00	1	605,609	0	107,956	0.15	1.00	5.61	1.00
0.05	321	8	0.02	322	605,288	8	107,948	0.15	1.00	5.61	1.00
0.10	4,933	133	0.03	5,255	600,355	141	107,815	0.15	1.00	5.56	0.99
0.15	22,198	731	0.03	27,453	578,157	872	107,084	0.16	0.99	5.36	0.96
0.20	36,746	1,768	0.05	64,199	541,411	2,640	105,316	0.16	0.98	5.02	0.91
0.25	45,782	2,756	0.06	109,981	495,629	5,396	102,560	0.17	0.95	4.59	0.84
0.30	53,176	4,122	0.07	163,157	442,453	9,518	98,438	0.18	0.91	4.10	0.76
0.35	60,091	5,760	0.09	223,248	382,362	15,278	92,678	0.20	0.86	3.54	0.67
0.40	65,151	7,572	0.10	288,399	317,211	22,850	85,106	0.21	0.79	2.94	0.56
0.45	64,815	9,321	0.13	353,214	252,396	32,171	75,785	0.23	0.70	2.34	0.46
0.50	61,114	10,517	0.15	414,328	191,282	42,688	65,268	0.25	0.60	1.77	0.36
0.55	52,931	11,061	0.17	467,259	138,351	53,749	54,207	0.28	0.50	1.28	0.27
0.60	42,163	10,599	0.20	509,422	96,188	64,348	43,608	0.31	0.40	0.89	0.20
0.65	32,107	9,595	0.23	541,529	64,081	73,943	34,013	0.35	0.32	0.59	0.14
0.70	22,439	8,235	0.27	563,968	41,642	82,178	25,778	0.38	0.24	0.39	0.09
0.75	15,064	6,871	0.31	579,032	26,578	89,049	18,907	0.42	0.18	0.25	0.06
0.80	10,668	5,971	0.36	589,700	15,910	95,020	12,936	0.45	0.12	0.15	0.04
0.85	7,896	5,472	0.41	597,596	8,014	100,492	7,464	0.48	0.07	0.07	0.02
0.90	5,550	4,840	0.47	603,146	2,464	105,332	2,624	0.52	0.02	0.02	0.01
0.95	2,271	2,378	0.51	605,417	193	107,710	246	0.56	0.00	0.00	0.00
1.00	193	246	0.56	605,610	0	107,956	0	nan	0.00	0.00	0.00

LogReg\_5\_Fold\_alpha\_balanced\_Medium\_Test\_Transformed\_98



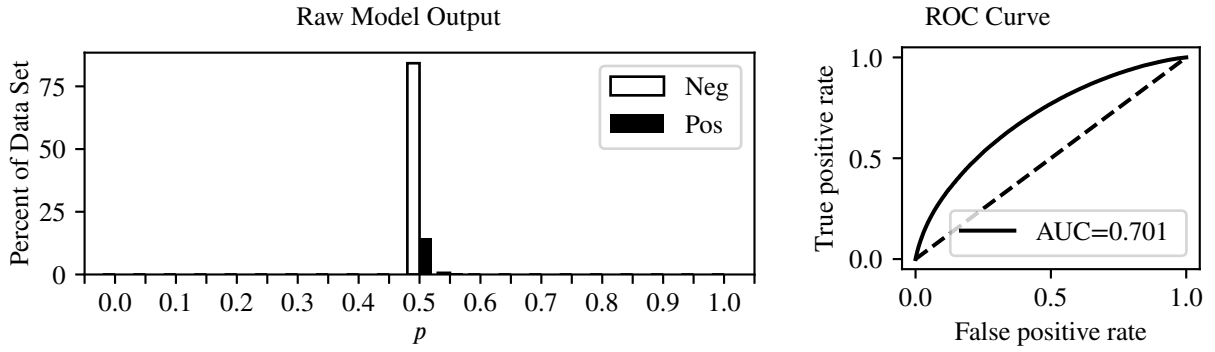
	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
p											
0.00	6,057	159	0.03	6,057	599,553	159	107,797	0.15	1.00	5.55	0.99
0.05	17,911	585	0.03	23,968	581,642	744	107,212	0.16	0.99	5.39	0.97
0.10	28,591	1,262	0.04	52,559	553,051	2,006	105,950	0.16	0.98	5.12	0.92
0.15	34,840	1,931	0.05	87,399	518,211	3,937	104,019	0.17	0.96	4.80	0.87
0.20	40,560	2,780	0.06	127,959	477,651	6,717	101,239	0.17	0.94	4.42	0.81
0.25	45,481	3,660	0.07	173,440	432,170	10,377	97,579	0.18	0.90	4.00	0.74
0.30	49,726	4,893	0.09	223,166	382,444	15,270	92,686	0.20	0.86	3.54	0.67
0.35	53,346	6,080	0.10	276,512	329,098	21,350	86,606	0.21	0.80	3.05	0.58
0.40	53,829	7,356	0.12	330,341	275,269	28,706	79,250	0.22	0.73	2.55	0.50
0.45	51,894	8,158	0.14	382,235	223,375	36,864	71,092	0.24	0.66	2.07	0.41
0.50	47,966	8,928	0.16	430,201	175,409	45,792	62,164	0.26	0.58	1.62	0.33
0.55	42,064	9,082	0.18	472,265	133,345	54,874	53,082	0.28	0.49	1.24	0.26
0.60	34,415	8,705	0.20	506,680	98,930	63,579	44,377	0.31	0.41	0.92	0.20
0.65	27,747	8,028	0.22	534,427	71,183	71,607	36,349	0.34	0.34	0.66	0.15
0.70	20,953	7,259	0.26	555,380	50,230	78,866	29,090	0.37	0.27	0.47	0.11
0.75	15,253	6,202	0.29	570,633	34,977	85,068	22,888	0.40	0.21	0.32	0.08
0.80	10,950	5,290	0.33	581,583	24,027	90,358	17,598	0.42	0.16	0.22	0.06
0.85	8,439	4,891	0.37	590,022	15,588	95,249	12,707	0.45	0.12	0.14	0.04
0.90	6,593	4,478	0.40	596,615	8,995	99,727	8,229	0.48	0.08	0.08	0.02
0.95	5,153	4,276	0.45	601,768	3,842	104,003	3,953	0.51	0.04	0.04	0.01
1.00	3,842	3,953	0.51	605,610	0	107,956	0	nan	0.00	0.00	0.00

LogReg\_5\_Fold\_alpha\_balanced\_Medium\_Test\_Transformed\_95



$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	15,141	412	0.03	15,141	590,469	412	107,544	0.15	1.00	5.47	0.98
0.05	23,481	911	0.04	38,622	566,988	1,323	106,633	0.16	0.99	5.25	0.94
0.10	29,896	1,562	0.05	68,518	537,092	2,885	105,071	0.16	0.97	4.98	0.90
0.15	35,232	2,094	0.06	103,750	501,860	4,979	102,977	0.17	0.95	4.65	0.85
0.20	39,698	2,933	0.07	143,448	462,162	7,912	100,044	0.18	0.93	4.28	0.79
0.25	43,980	3,745	0.08	187,428	418,182	11,657	96,299	0.19	0.89	3.87	0.72
0.30	47,607	4,892	0.09	235,035	370,575	16,549	91,407	0.20	0.85	3.43	0.65
0.35	50,620	5,976	0.11	285,655	319,955	22,525	85,431	0.21	0.79	2.96	0.57
0.40	50,292	7,003	0.12	335,947	269,663	29,528	78,428	0.23	0.73	2.50	0.49
0.45	48,424	7,714	0.14	384,371	221,239	37,242	70,714	0.24	0.66	2.05	0.41
0.50	45,011	8,372	0.16	429,382	176,228	45,614	62,342	0.26	0.58	1.63	0.33
0.55	39,848	8,578	0.18	469,230	136,380	54,192	53,764	0.28	0.50	1.26	0.27
0.60	33,006	8,154	0.20	502,236	103,374	62,346	45,610	0.31	0.42	0.96	0.21
0.65	27,028	7,776	0.22	529,264	76,346	70,122	37,834	0.33	0.35	0.71	0.16
0.70	21,132	6,952	0.25	550,396	55,214	77,074	30,882	0.36	0.29	0.51	0.12
0.75	15,811	6,054	0.28	566,207	39,403	83,128	24,828	0.39	0.23	0.36	0.09
0.80	11,563	5,308	0.31	577,770	27,840	88,436	19,520	0.41	0.18	0.26	0.07
0.85	8,822	4,598	0.34	586,592	19,018	93,034	14,922	0.44	0.14	0.18	0.05
0.90	6,813	4,405	0.39	593,405	12,205	97,439	10,517	0.46	0.10	0.11	0.03
0.95	5,604	4,154	0.43	599,009	6,601	101,593	6,363	0.49	0.06	0.06	0.02
1.00	6,601	6,363	0.49	605,610	0	107,956	0	nan	0.00	0.00	0.00

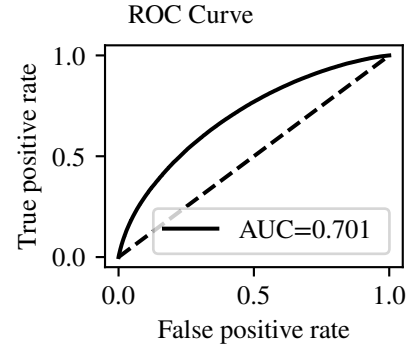
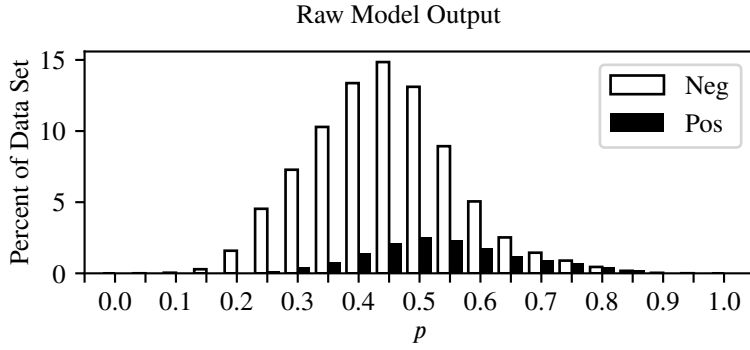
AdaBoost\_5\_Fold\_Medium\_Test



	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
$p$											
0.00	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.05	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.10	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.15	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.20	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.25	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.30	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.35	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.40	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.45	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.50	600,973	103,240	0.15	600,973	4,637	103,240	4,716	0.50	0.04	0.04	0.01
0.55	4,637	4,716	0.50	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.60	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.65	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.70	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.75	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.80	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.85	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.90	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.95	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
1.00	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00

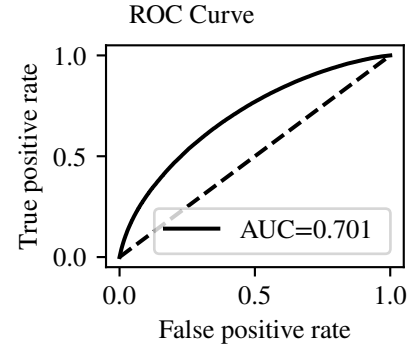
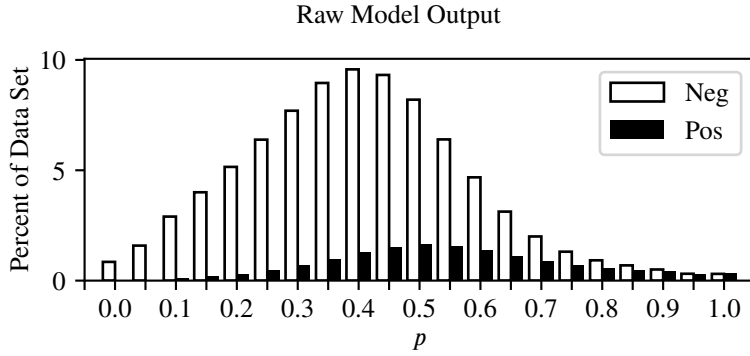


AdaBoost\_5\_Fold\_Medium\_Test\_Transformed\_100



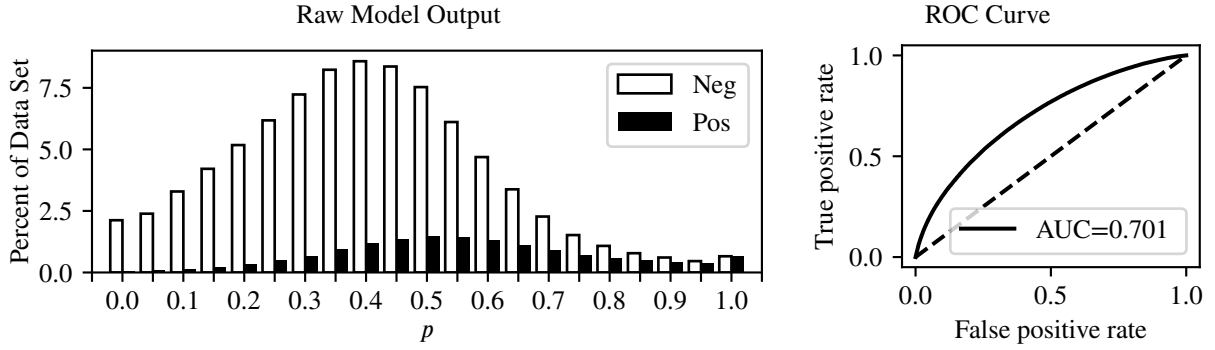
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	1	0	0.00	1	605,609	0	107,956	0.15	1.00	5.61	1.00
0.05	16	1	0.06	17	605,593	1	107,955	0.15	1.00	5.61	1.00
0.10	296	8	0.03	313	605,297	9	107,947	0.15	1.00	5.61	1.00
0.15	2,048	43	0.02	2,361	603,249	52	107,904	0.15	1.00	5.59	1.00
0.20	11,333	321	0.03	13,694	591,916	373	107,583	0.15	1.00	5.48	0.98
0.25	32,363	1,307	0.04	46,057	559,553	1,680	106,276	0.16	0.98	5.18	0.93
0.30	51,951	2,897	0.05	98,008	507,602	4,577	103,379	0.17	0.96	4.70	0.86
0.35	73,419	5,685	0.07	171,427	434,183	10,262	97,694	0.18	0.90	4.02	0.75
0.40	95,401	9,906	0.09	266,828	338,782	20,168	87,788	0.21	0.81	3.14	0.60
0.45	105,957	15,143	0.13	372,785	232,825	35,311	72,645	0.24	0.67	2.16	0.43
0.50	93,548	18,261	0.16	466,333	139,277	53,572	54,384	0.28	0.50	1.29	0.27
0.55	63,762	16,774	0.21	530,095	75,515	70,346	37,610	0.33	0.35	0.70	0.16
0.60	36,068	12,739	0.26	566,163	39,447	83,085	24,871	0.39	0.23	0.37	0.09
0.65	18,008	8,627	0.32	584,171	21,439	91,712	16,244	0.43	0.15	0.20	0.05
0.70	10,338	6,427	0.38	594,509	11,101	98,139	9,817	0.47	0.09	0.10	0.03
0.75	6,372	5,019	0.44	600,881	4,729	103,158	4,798	0.50	0.04	0.04	0.01
0.80	3,196	3,067	0.49	604,077	1,533	106,225	1,731	0.53	0.02	0.01	0.00
0.85	1,254	1,358	0.52	605,331	279	107,583	373	0.57	0.00	0.00	0.00
0.90	243	320	0.57	605,574	36	107,903	53	0.60	0.00	0.00	0.00
0.95	35	50	0.59	605,609	1	107,953	3	0.75	0.00	0.00	0.00
1.00	1	3	0.75	605,610	0	107,956	0	nan	0.00	0.00	0.00

AdaBoost\_5\_Fold\_Medium\_Test\_Transformed\_98



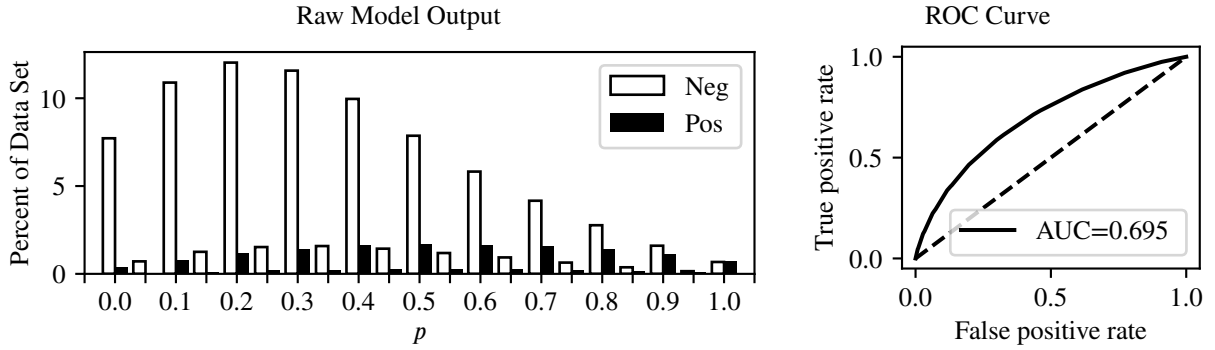
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	6,057	164	0.03	6,057	599,553	164	107,792	0.15	1.00	5.55	0.99
0.05	11,323	317	0.03	17,380	588,230	481	107,475	0.15	1.00	5.45	0.97
0.10	20,702	818	0.04	38,082	567,528	1,299	106,657	0.16	0.99	5.26	0.94
0.15	28,562	1,476	0.05	66,644	538,966	2,775	105,181	0.16	0.97	4.99	0.90
0.20	36,768	2,176	0.06	103,412	502,198	4,951	103,005	0.17	0.95	4.65	0.85
0.25	45,578	3,403	0.07	148,990	456,620	8,354	99,602	0.18	0.92	4.23	0.78
0.30	54,929	4,922	0.08	203,919	401,691	13,276	94,680	0.19	0.88	3.72	0.70
0.35	63,903	7,042	0.10	267,822	337,788	20,318	87,638	0.21	0.81	3.13	0.60
0.40	68,302	9,241	0.12	336,124	269,486	29,559	78,397	0.23	0.73	2.50	0.49
0.45	66,494	10,972	0.14	402,618	202,992	40,531	67,425	0.25	0.62	1.88	0.38
0.50	58,508	11,841	0.17	461,126	144,484	52,372	55,584	0.28	0.51	1.34	0.28
0.55	45,655	11,254	0.20	506,781	98,829	63,626	44,330	0.31	0.41	0.92	0.20
0.60	33,390	9,902	0.23	540,171	65,439	73,528	34,428	0.34	0.32	0.61	0.14
0.65	22,315	8,020	0.26	562,486	43,124	81,548	26,408	0.38	0.24	0.40	0.10
0.70	14,276	6,352	0.31	576,762	28,848	87,900	20,056	0.41	0.19	0.27	0.07
0.75	9,353	4,887	0.34	586,115	19,495	92,787	15,169	0.44	0.14	0.18	0.05
0.80	6,567	4,138	0.39	592,682	12,928	96,925	11,031	0.46	0.10	0.12	0.03
0.85	4,929	3,508	0.42	597,611	7,999	100,433	7,523	0.48	0.07	0.07	0.02
0.90	3,601	3,015	0.46	601,212	4,398	103,448	4,508	0.51	0.04	0.04	0.01
0.95	2,218	2,164	0.49	603,430	2,180	105,612	2,344	0.52	0.02	0.02	0.01
1.00	2,180	2,344	0.52	605,610	0	107,956	0	nan	0.00	0.00	0.00

AdaBoost\_5\_Fold\_Medium\_Test\_Transformed\_95



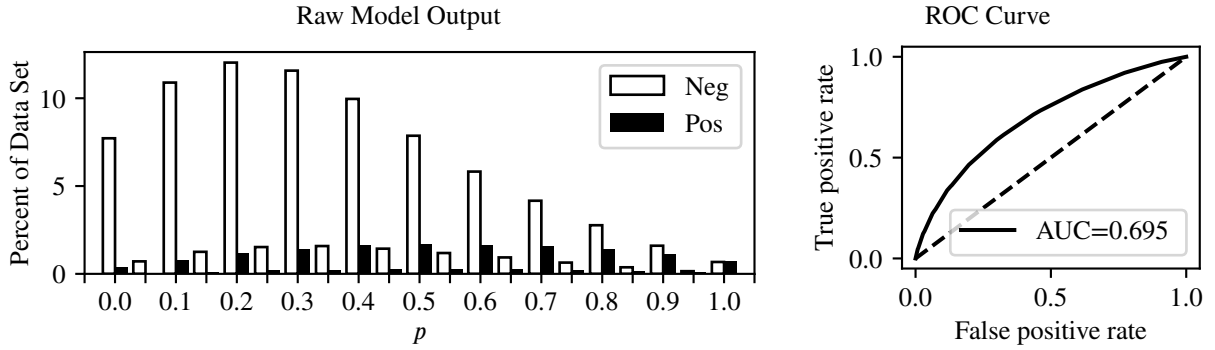
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	15,142	413	0.03	15,142	590,468	413	107,543	0.15	1.00	5.47	0.98
0.05	17,042	634	0.04	32,184	573,426	1,047	106,909	0.16	0.99	5.31	0.95
0.10	23,477	1,131	0.05	55,661	549,949	2,178	105,778	0.16	0.98	5.09	0.92
0.15	30,046	1,675	0.05	85,707	519,903	3,853	104,103	0.17	0.96	4.82	0.87
0.20	36,932	2,503	0.06	122,639	482,971	6,356	101,600	0.17	0.94	4.47	0.82
0.25	44,092	3,492	0.07	166,731	438,879	9,848	98,108	0.18	0.91	4.07	0.75
0.30	51,599	4,904	0.09	218,330	387,280	14,752	93,204	0.19	0.86	3.59	0.67
0.35	58,760	6,701	0.10	277,090	328,520	21,453	86,503	0.21	0.80	3.04	0.58
0.40	61,234	8,443	0.12	338,324	267,286	29,896	78,060	0.23	0.72	2.48	0.48
0.45	59,701	9,785	0.14	398,025	207,585	39,681	68,275	0.25	0.63	1.92	0.39
0.50	53,736	10,511	0.16	451,761	153,849	50,192	57,764	0.27	0.54	1.43	0.30
0.55	43,609	10,389	0.19	495,370	110,240	60,581	47,375	0.30	0.44	1.02	0.22
0.60	33,453	9,393	0.22	528,823	76,787	69,974	37,982	0.33	0.35	0.71	0.16
0.65	24,103	7,988	0.25	552,926	52,684	77,962	29,994	0.36	0.28	0.49	0.12
0.70	16,213	6,394	0.28	569,139	36,471	84,356	23,600	0.39	0.22	0.34	0.08
0.75	10,845	5,120	0.32	579,984	25,626	89,476	18,480	0.42	0.17	0.24	0.06
0.80	7,705	4,218	0.35	587,689	17,921	93,694	14,262	0.44	0.13	0.17	0.05
0.85	5,587	3,628	0.39	593,276	12,334	97,322	10,634	0.46	0.10	0.11	0.03
0.90	4,338	3,112	0.42	597,614	7,996	100,434	7,522	0.48	0.07	0.07	0.02
0.95	3,296	2,747	0.45	600,910	4,700	103,181	4,775	0.50	0.04	0.04	0.01
1.00	4,700	4,775	0.50	605,610	0	107,956	0	nan	0.00	0.00	0.00

BalBag\_5\_Fold\_Medium\_Test



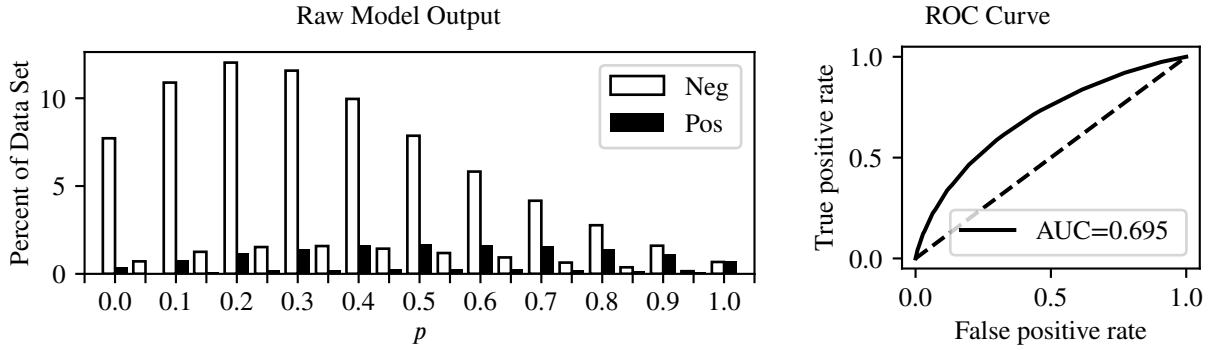
	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
p											
0.00	55,088	2,730	0.05	55,088	550,522	2,730	105,226	0.16	0.97	5.10	0.92
0.05	5,072	332	0.06	60,160	545,450	3,062	104,894	0.16	0.97	5.05	0.91
0.10	77,722	5,515	0.07	137,882	467,728	8,577	99,379	0.18	0.92	4.33	0.79
0.15	8,947	769	0.08	146,829	458,781	9,346	98,610	0.18	0.91	4.25	0.78
0.20	85,840	8,177	0.09	232,669	372,941	17,523	90,433	0.20	0.84	3.45	0.65
0.25	10,889	1,252	0.10	243,558	362,052	18,775	89,181	0.20	0.83	3.35	0.63
0.30	82,574	9,995	0.11	326,132	279,478	28,770	79,186	0.22	0.73	2.59	0.50
0.35	11,300	1,552	0.12	337,432	268,178	30,322	77,634	0.22	0.72	2.48	0.48
0.40	71,081	11,455	0.14	408,513	197,097	41,777	66,179	0.25	0.61	1.83	0.37
0.45	10,230	1,822	0.15	418,743	186,867	43,599	64,357	0.26	0.60	1.73	0.35
0.50	56,121	11,841	0.17	474,864	130,746	55,440	52,516	0.29	0.49	1.21	0.26
0.55	8,467	1,731	0.17	483,331	122,279	57,171	50,785	0.29	0.47	1.13	0.24
0.60	41,556	11,700	0.22	524,887	80,723	68,871	39,085	0.33	0.36	0.75	0.17
0.65	6,676	1,682	0.20	531,563	74,047	70,553	37,403	0.34	0.35	0.69	0.16
0.70	29,711	11,252	0.27	561,274	44,336	81,805	26,151	0.37	0.24	0.41	0.10
0.75	4,577	1,486	0.25	565,851	39,759	83,291	24,665	0.38	0.23	0.37	0.09
0.80	19,755	10,092	0.34	585,606	20,004	93,383	14,573	0.42	0.13	0.19	0.05
0.85	2,663	1,130	0.30	588,269	17,341	94,513	13,443	0.44	0.12	0.16	0.04
0.90	11,434	7,953	0.41	599,703	5,907	102,466	5,490	0.48	0.05	0.05	0.02
0.95	1,080	555	0.34	600,783	4,827	103,021	4,935	0.51	0.05	0.04	0.01
1.00	4,827	4,935	0.51	605,610	0	107,956	0	nan	0.00	0.00	0.00

BalBag\_5\_Fold\_Medium\_Test\_Transformed\_100



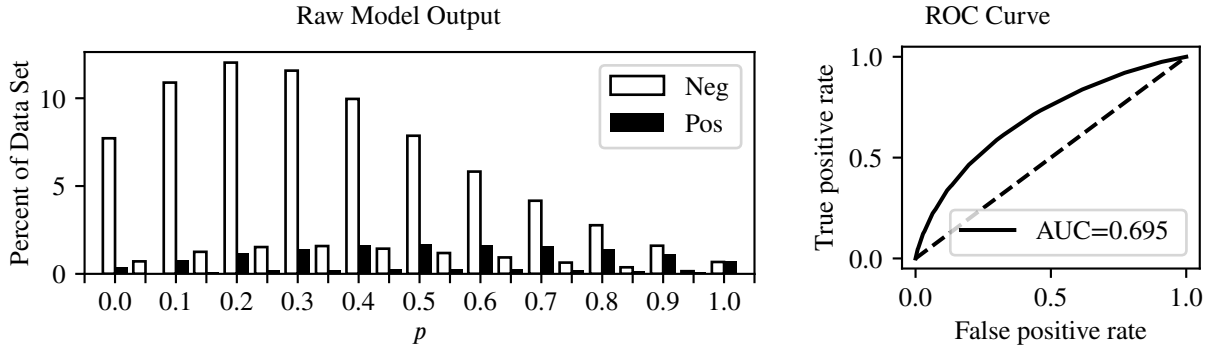
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	55,088	2,730	0.05	55,088	550,522	2,730	105,226	0.16	0.97	5.10	0.92
0.05	5,072	332	0.06	60,160	545,450	3,062	104,894	0.16	0.97	5.05	0.91
0.10	77,722	5,515	0.07	137,882	467,728	8,577	99,379	0.18	0.92	4.33	0.79
0.15	8,947	769	0.08	146,829	458,781	9,346	98,610	0.18	0.91	4.25	0.78
0.20	85,840	8,177	0.09	232,669	372,941	17,523	90,433	0.20	0.84	3.45	0.65
0.25	10,889	1,252	0.10	243,558	362,052	18,775	89,181	0.20	0.83	3.35	0.63
0.30	82,574	9,995	0.11	326,132	279,478	28,770	79,186	0.22	0.73	2.59	0.50
0.35	11,300	1,552	0.12	337,432	268,178	30,322	77,634	0.22	0.72	2.48	0.48
0.40	71,081	11,455	0.14	408,513	197,097	41,777	66,179	0.25	0.61	1.83	0.37
0.45	10,230	1,822	0.15	418,743	186,867	43,599	64,357	0.26	0.60	1.73	0.35
0.50	56,121	11,841	0.17	474,864	130,746	55,440	52,516	0.29	0.49	1.21	0.26
0.55	8,467	1,731	0.17	483,331	122,279	57,171	50,785	0.29	0.47	1.13	0.24
0.60	41,556	11,700	0.22	524,887	80,723	68,871	39,085	0.33	0.36	0.75	0.17
0.65	6,676	1,682	0.20	531,563	74,047	70,553	37,403	0.34	0.35	0.69	0.16
0.70	29,711	11,252	0.27	561,274	44,336	81,805	26,151	0.37	0.24	0.41	0.10
0.75	4,577	1,486	0.25	565,851	39,759	83,291	24,665	0.38	0.23	0.37	0.09
0.80	19,755	10,092	0.34	585,606	20,004	93,383	14,573	0.42	0.13	0.19	0.05
0.85	2,663	1,130	0.30	588,269	17,341	94,513	13,443	0.44	0.12	0.16	0.04
0.90	11,434	7,953	0.41	599,703	5,907	102,466	5,490	0.48	0.05	0.05	0.02
0.95	1,080	555	0.34	600,783	4,827	103,021	4,935	0.51	0.05	0.04	0.01
1.00	4,827	4,935	0.51	605,610	0	107,956	0	nan	0.00	0.00	0.00

BalBag\_5\_Fold\_Medium\_Test\_Transformed\_98



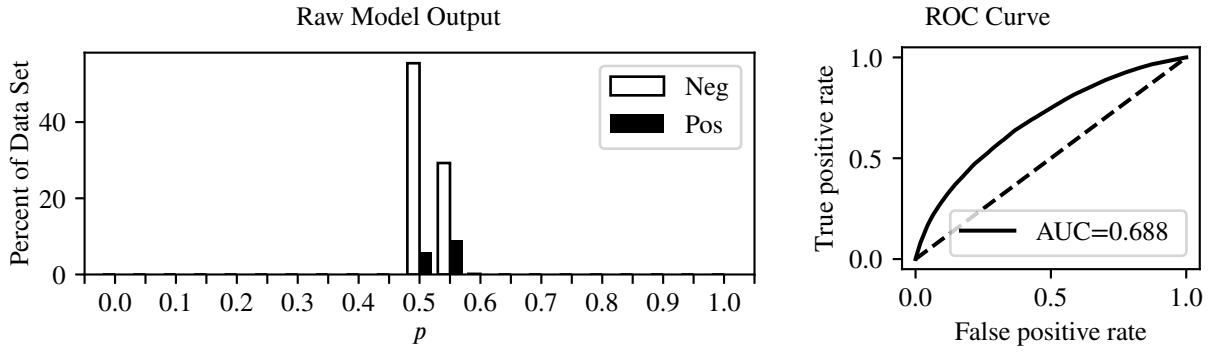
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	55,088	2,730	0.05	55,088	550,522	2,730	105,226	0.16	0.97	5.10	0.92
0.05	5,072	332	0.06	60,160	545,450	3,062	104,894	0.16	0.97	5.05	0.91
0.10	77,722	5,515	0.07	137,882	467,728	8,577	99,379	0.18	0.92	4.33	0.79
0.15	8,947	769	0.08	146,829	458,781	9,346	98,610	0.18	0.91	4.25	0.78
0.20	85,840	8,177	0.09	232,669	372,941	17,523	90,433	0.20	0.84	3.45	0.65
0.25	10,889	1,252	0.10	243,558	362,052	18,775	89,181	0.20	0.83	3.35	0.63
0.30	82,574	9,995	0.11	326,132	279,478	28,770	79,186	0.22	0.73	2.59	0.50
0.35	11,300	1,552	0.12	337,432	268,178	30,322	77,634	0.22	0.72	2.48	0.48
0.40	71,081	11,455	0.14	408,513	197,097	41,777	66,179	0.25	0.61	1.83	0.37
0.45	10,230	1,822	0.15	418,743	186,867	43,599	64,357	0.26	0.60	1.73	0.35
0.50	56,121	11,841	0.17	474,864	130,746	55,440	52,516	0.29	0.49	1.21	0.26
0.55	8,467	1,731	0.17	483,331	122,279	57,171	50,785	0.29	0.47	1.13	0.24
0.60	41,556	11,700	0.22	524,887	80,723	68,871	39,085	0.33	0.36	0.75	0.17
0.65	6,676	1,682	0.20	531,563	74,047	70,553	37,403	0.34	0.35	0.69	0.16
0.70	29,711	11,252	0.27	561,274	44,336	81,805	26,151	0.37	0.24	0.41	0.10
0.75	4,577	1,486	0.25	565,851	39,759	83,291	24,665	0.38	0.23	0.37	0.09
0.80	19,755	10,092	0.34	585,606	20,004	93,383	14,573	0.42	0.13	0.19	0.05
0.85	2,663	1,130	0.30	588,269	17,341	94,513	13,443	0.44	0.12	0.16	0.04
0.90	11,434	7,953	0.41	599,703	5,907	102,466	5,490	0.48	0.05	0.05	0.02
0.95	1,080	555	0.34	600,783	4,827	103,021	4,935	0.51	0.05	0.04	0.01
1.00	4,827	4,935	0.51	605,610	0	107,956	0	nan	0.00	0.00	0.00

BalBag\_5\_Fold\_Medium\_Test\_Transformed\_95



$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	55,088	2,730	0.05	55,088	550,522	2,730	105,226	0.16	0.97	5.10	0.92
0.05	5,072	332	0.06	60,160	545,450	3,062	104,894	0.16	0.97	5.05	0.91
0.10	77,722	5,515	0.07	137,882	467,728	8,577	99,379	0.18	0.92	4.33	0.79
0.15	8,947	769	0.08	146,829	458,781	9,346	98,610	0.18	0.91	4.25	0.78
0.20	85,840	8,177	0.09	232,669	372,941	17,523	90,433	0.20	0.84	3.45	0.65
0.25	10,889	1,252	0.10	243,558	362,052	18,775	89,181	0.20	0.83	3.35	0.63
0.30	82,574	9,995	0.11	326,132	279,478	28,770	79,186	0.22	0.73	2.59	0.50
0.35	11,300	1,552	0.12	337,432	268,178	30,322	77,634	0.22	0.72	2.48	0.48
0.40	71,081	11,455	0.14	408,513	197,097	41,777	66,179	0.25	0.61	1.83	0.37
0.45	10,230	1,822	0.15	418,743	186,867	43,599	64,357	0.26	0.60	1.73	0.35
0.50	56,121	11,841	0.17	474,864	130,746	55,440	52,516	0.29	0.49	1.21	0.26
0.55	8,467	1,731	0.17	483,331	122,279	57,171	50,785	0.29	0.47	1.13	0.24
0.60	41,556	11,700	0.22	524,887	80,723	68,871	39,085	0.33	0.36	0.75	0.17
0.65	6,676	1,682	0.20	531,563	74,047	70,553	37,403	0.34	0.35	0.69	0.16
0.70	29,711	11,252	0.27	561,274	44,336	81,805	26,151	0.37	0.24	0.41	0.10
0.75	4,577	1,486	0.25	565,851	39,759	83,291	24,665	0.38	0.23	0.37	0.09
0.80	19,755	10,092	0.34	585,606	20,004	93,383	14,573	0.42	0.13	0.19	0.05
0.85	2,663	1,130	0.30	588,269	17,341	94,513	13,443	0.44	0.12	0.16	0.04
0.90	11,434	7,953	0.41	599,703	5,907	102,466	5,490	0.48	0.05	0.05	0.02
0.95	1,080	555	0.34	600,783	4,827	103,021	4,935	0.51	0.05	0.04	0.01
1.00	4,827	4,935	0.51	605,610	0	107,956	0	nan	0.00	0.00	0.00

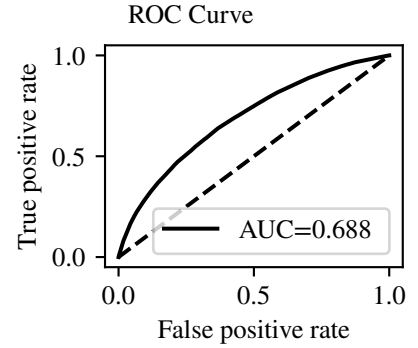
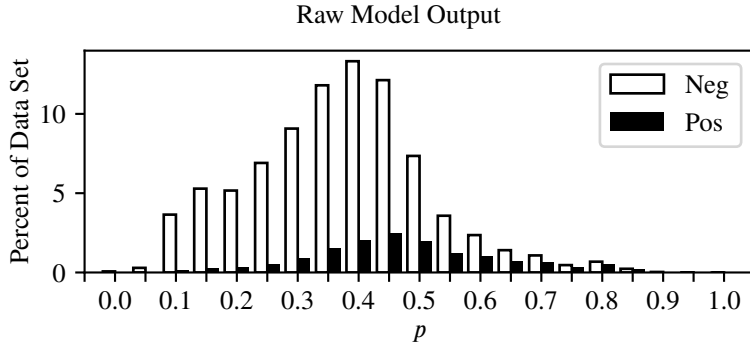
EEC\_5\_Fold\_Medium\_Test



$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.05	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.10	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.15	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.20	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.25	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.30	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.35	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.40	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.45	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.50	395,729	41,594	0.10	395,729	209,881	41,594	66,362	0.24	0.61	1.94	0.39
0.55	208,776	65,228	0.24	604,505	1,105	106,822	1,134	0.51	0.01	0.01	0.00
0.60	1,105	1,134	0.51	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.65	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.70	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.75	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.80	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.85	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.90	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.95	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
1.00	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00

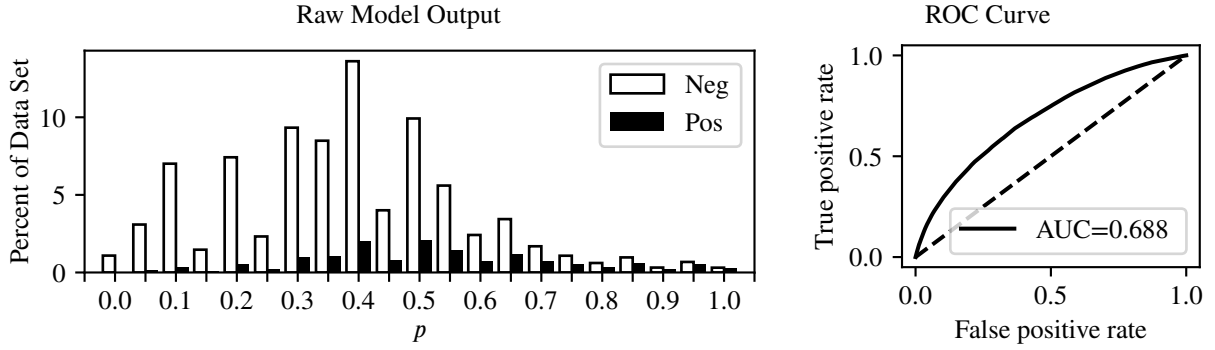


EEC\_5\_Fold\_Medium\_Test\_Transformed\_100



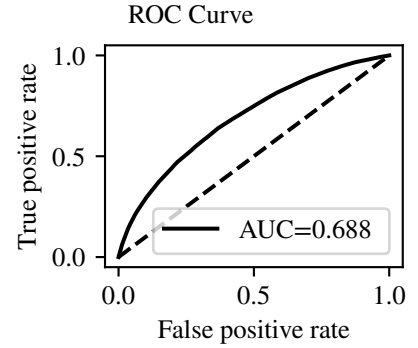
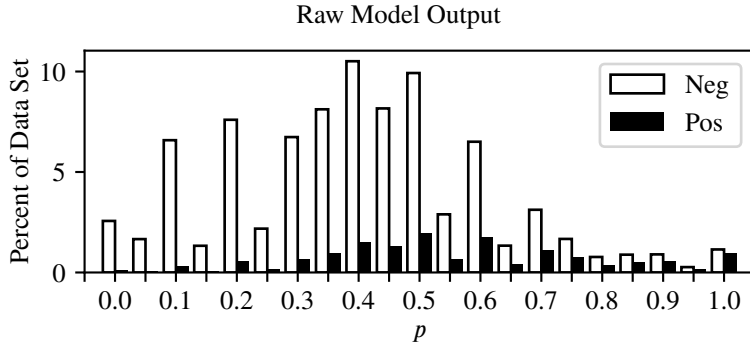
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	487	18	0.04	487	605,123	18	107,938	0.15	1.00	5.61	1.00
0.05	2,077	62	0.03	2,564	603,046	80	107,876	0.15	1.00	5.59	1.00
0.10	26,033	1,091	0.04	28,597	577,013	1,171	106,785	0.16	0.99	5.34	0.96
0.15	37,721	1,979	0.05	66,318	539,292	3,150	104,806	0.16	0.97	5.00	0.90
0.20	36,861	2,337	0.06	103,179	502,431	5,487	102,469	0.17	0.95	4.65	0.85
0.25	49,283	3,912	0.07	152,462	453,148	9,399	98,557	0.18	0.91	4.20	0.77
0.30	64,743	6,660	0.09	217,205	388,405	16,059	91,897	0.19	0.85	3.60	0.67
0.35	84,216	10,828	0.11	301,421	304,189	26,887	81,069	0.21	0.75	2.82	0.54
0.40	95,050	14,830	0.13	396,471	209,139	41,717	66,239	0.24	0.61	1.94	0.39
0.45	86,542	17,640	0.17	483,013	122,597	59,357	48,599	0.28	0.45	1.14	0.24
0.50	52,443	14,179	0.21	535,456	70,154	73,536	34,420	0.33	0.32	0.65	0.15
0.55	25,532	8,759	0.26	560,988	44,622	82,295	25,661	0.37	0.24	0.41	0.10
0.60	16,822	7,195	0.30	577,810	27,800	89,490	18,466	0.40	0.17	0.26	0.06
0.65	10,035	5,360	0.35	587,845	17,765	94,850	13,106	0.42	0.12	0.16	0.04
0.70	7,676	4,860	0.39	595,521	10,089	99,710	8,246	0.45	0.08	0.09	0.03
0.75	3,319	2,477	0.43	598,840	6,770	102,187	5,769	0.46	0.05	0.06	0.02
0.80	4,856	3,904	0.45	603,696	1,914	106,091	1,865	0.49	0.02	0.02	0.01
0.85	1,660	1,547	0.48	605,356	254	107,638	318	0.56	0.00	0.00	0.00
0.90	234	298	0.56	605,590	20	107,936	20	0.50	0.00	0.00	0.00
0.95	18	17	0.49	605,608	2	107,953	3	0.60	0.00	0.00	0.00
1.00	2	3	0.60	605,610	0	107,956	0	nan	0.00	0.00	0.00

EEC\_5\_Fold\_Medium\_Test\_Transformed\_98



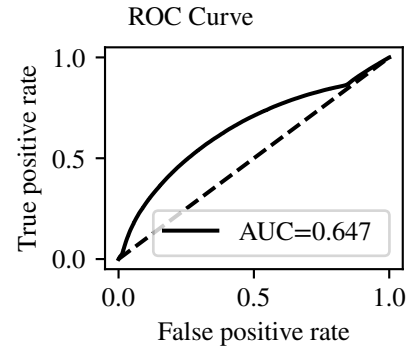
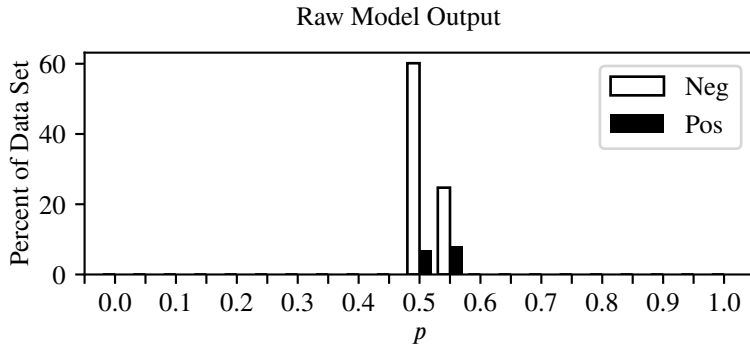
	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
p											
0.00	7,763	310	0.04	7,763	597,847	310	107,646	0.15	1.00	5.54	0.99
0.05	22,039	933	0.04	29,802	575,808	1,243	106,713	0.16	0.99	5.33	0.96
0.10	50,021	2,613	0.05	79,823	525,787	3,856	104,100	0.17	0.96	4.87	0.88
0.15	10,477	794	0.07	90,300	515,310	4,650	103,306	0.17	0.96	4.77	0.87
0.20	52,961	3,971	0.07	143,261	462,349	8,621	99,335	0.18	0.92	4.28	0.79
0.25	16,559	1,487	0.08	159,820	445,790	10,108	97,848	0.18	0.91	4.13	0.76
0.30	66,579	6,992	0.10	226,399	379,211	17,100	90,856	0.19	0.84	3.51	0.66
0.35	60,581	7,730	0.11	286,980	318,630	24,830	83,126	0.21	0.77	2.95	0.56
0.40	97,130	14,369	0.13	384,110	221,500	39,199	68,757	0.24	0.64	2.05	0.41
0.45	28,596	5,561	0.16	412,706	192,904	44,760	63,196	0.25	0.59	1.79	0.36
0.50	70,804	14,756	0.17	483,510	122,100	59,516	48,440	0.28	0.45	1.13	0.24
0.55	39,958	10,448	0.21	523,468	82,142	69,964	37,992	0.32	0.35	0.76	0.17
0.60	17,245	5,280	0.23	540,713	64,897	75,244	32,712	0.34	0.30	0.60	0.14
0.65	24,540	8,575	0.26	565,253	40,357	83,819	24,137	0.37	0.22	0.37	0.09
0.70	12,044	5,406	0.31	577,297	28,313	89,225	18,731	0.40	0.17	0.26	0.07
0.75	7,706	3,955	0.34	585,003	20,607	93,180	14,776	0.42	0.14	0.19	0.05
0.80	4,362	2,586	0.37	589,365	16,245	95,766	12,190	0.43	0.11	0.15	0.04
0.85	6,931	4,495	0.39	596,296	9,314	100,261	7,695	0.45	0.07	0.09	0.02
0.90	2,257	1,641	0.42	598,553	7,057	101,902	6,054	0.46	0.06	0.07	0.02
0.95	4,846	3,915	0.45	603,399	2,211	105,817	2,139	0.49	0.02	0.02	0.01
1.00	2,211	2,139	0.49	605,610	0	107,956	0	nan	0.00	0.00	0.00

EEC\_5\_Fold\_Medium\_Test\_Transformed\_95



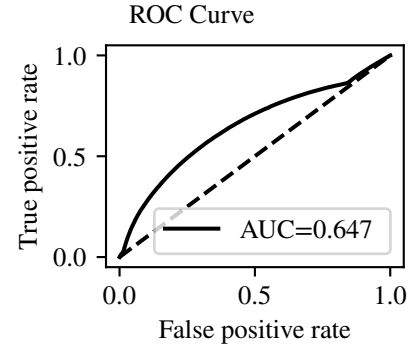
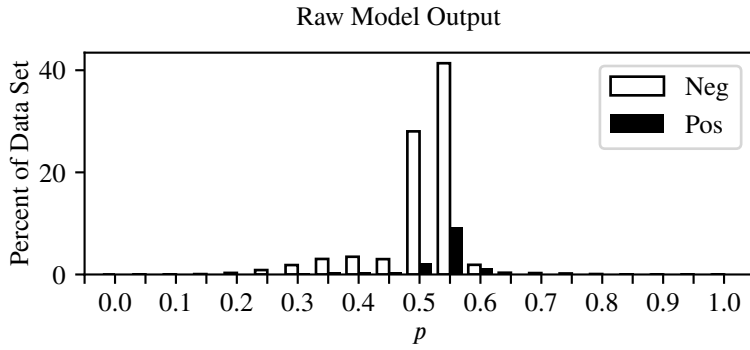
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	18,299	771	0.04	18,299	587,311	771	107,185	0.15	0.99	5.44	0.97
0.05	11,850	486	0.04	30,149	575,461	1,257	106,699	0.16	0.99	5.33	0.96
0.10	46,969	2,445	0.05	77,118	528,492	3,702	104,254	0.16	0.97	4.90	0.89
0.15	9,482	684	0.07	86,600	519,010	4,386	103,570	0.17	0.96	4.81	0.87
0.20	54,222	4,062	0.07	140,822	464,788	8,448	99,508	0.18	0.92	4.31	0.79
0.25	15,566	1,361	0.08	156,388	449,222	9,809	98,147	0.18	0.91	4.16	0.77
0.30	48,077	4,760	0.09	204,465	401,145	14,569	93,387	0.19	0.87	3.72	0.69
0.35	57,937	6,904	0.11	262,402	343,208	21,473	86,483	0.20	0.80	3.18	0.60
0.40	75,012	10,679	0.12	337,414	268,196	32,152	75,804	0.22	0.70	2.48	0.48
0.45	58,256	9,434	0.14	395,670	209,940	41,586	66,370	0.24	0.61	1.94	0.39
0.50	70,822	13,982	0.16	466,492	139,118	55,568	52,388	0.27	0.49	1.29	0.27
0.55	20,645	4,909	0.19	487,137	118,473	60,477	47,479	0.29	0.44	1.10	0.23
0.60	46,425	12,433	0.21	533,562	72,048	72,910	35,046	0.33	0.32	0.67	0.15
0.65	9,524	3,049	0.24	543,086	62,524	75,959	31,997	0.34	0.30	0.58	0.13
0.70	22,270	7,892	0.26	565,356	40,254	83,851	24,105	0.37	0.22	0.37	0.09
0.75	11,911	5,361	0.31	577,267	28,343	89,212	18,744	0.40	0.17	0.26	0.07
0.80	5,506	2,679	0.33	582,773	22,837	91,891	16,065	0.41	0.15	0.21	0.05
0.85	6,323	3,709	0.37	589,096	16,514	95,600	12,356	0.43	0.11	0.15	0.04
0.90	6,427	4,111	0.39	595,523	10,087	99,711	8,245	0.45	0.08	0.09	0.03
0.95	1,909	1,337	0.41	597,432	8,178	101,048	6,908	0.46	0.06	0.08	0.02
1.00	8,178	6,908	0.46	605,610	0	107,956	0	nan	0.00	0.00	0.00

RUSBoost\_5\_Fold\_Medium\_Test



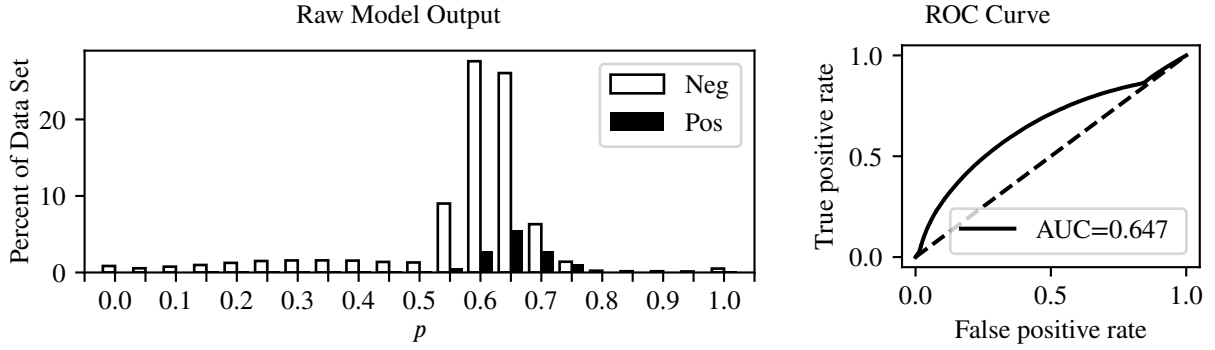
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.05	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.10	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.15	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.20	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.25	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.30	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.35	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.40	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.45	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.50	429,223	50,005	0.10	429,223	176,387	50,005	57,951	0.25	0.54	1.63	0.33
0.55	176,387	57,951	0.25	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.60	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.65	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.70	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.75	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.80	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.85	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.90	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.95	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
1.00	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00

RUSBoost\_5\_Fold\_Medium\_Test\_Transformed\_100



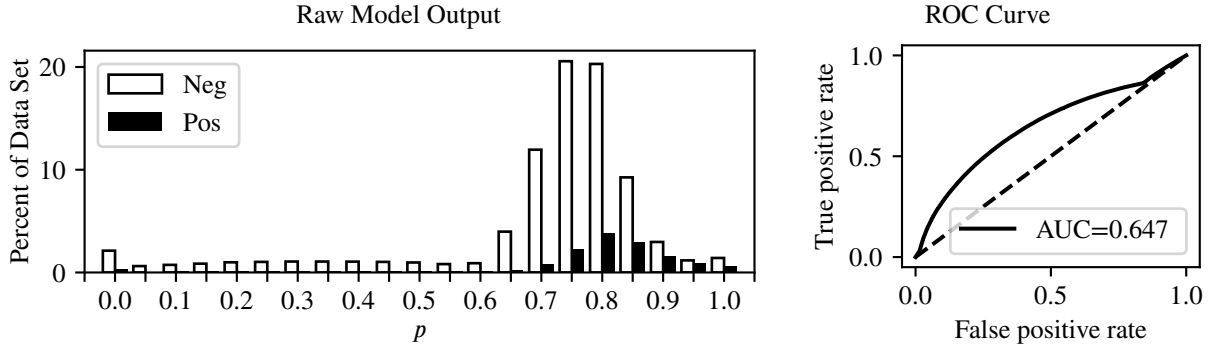
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	1	0	0.00	1	605,609	0	107,956	0.15	1.00	5.61	1.00
0.05	9	0	0.00	10	605,600	0	107,956	0.15	1.00	5.61	1.00
0.10	94	10	0.10	104	605,506	10	107,946	0.15	1.00	5.61	1.00
0.15	548	81	0.13	652	604,958	91	107,865	0.15	1.00	5.60	1.00
0.20	2,205	299	0.12	2,857	602,753	390	107,566	0.15	1.00	5.58	1.00
0.25	6,184	845	0.12	9,041	596,569	1,235	106,721	0.15	0.99	5.53	0.99
0.30	13,165	1,857	0.12	22,206	583,404	3,092	104,864	0.15	0.97	5.40	0.96
0.35	21,688	3,104	0.13	43,894	561,716	6,196	101,760	0.15	0.94	5.20	0.93
0.40	24,761	3,815	0.13	68,655	536,955	10,011	97,945	0.15	0.91	4.97	0.89
0.45	21,453	3,836	0.15	90,108	515,502	13,847	94,109	0.15	0.87	4.78	0.85
0.50	200,004	15,927	0.07	290,112	315,498	29,774	78,182	0.20	0.72	2.92	0.55
0.55	295,230	66,386	0.18	585,342	20,268	96,160	11,796	0.37	0.11	0.19	0.04
0.60	13,506	9,444	0.41	598,848	6,762	105,604	2,352	0.26	0.02	0.06	0.01
0.65	2,461	748	0.23	601,309	4,301	106,352	1,604	0.27	0.01	0.04	0.01
0.70	1,982	657	0.25	603,291	2,319	107,009	947	0.29	0.01	0.02	0.00
0.75	1,418	531	0.27	604,709	901	107,540	416	0.32	0.00	0.01	0.00
0.80	637	294	0.32	605,346	264	107,834	122	0.32	0.00	0.00	0.00
0.85	182	97	0.35	605,528	82	107,931	25	0.23	0.00	0.00	0.00
0.90	53	14	0.21	605,581	29	107,945	11	0.28	0.00	0.00	0.00
0.95	18	7	0.28	605,599	11	107,952	4	0.27	0.00	0.00	0.00
1.00	11	4	0.27	605,610	0	107,956	0	nan	0.00	0.00	0.00

RUSBoost\_5\_Fold\_Medium\_Test\_Transformed\_98



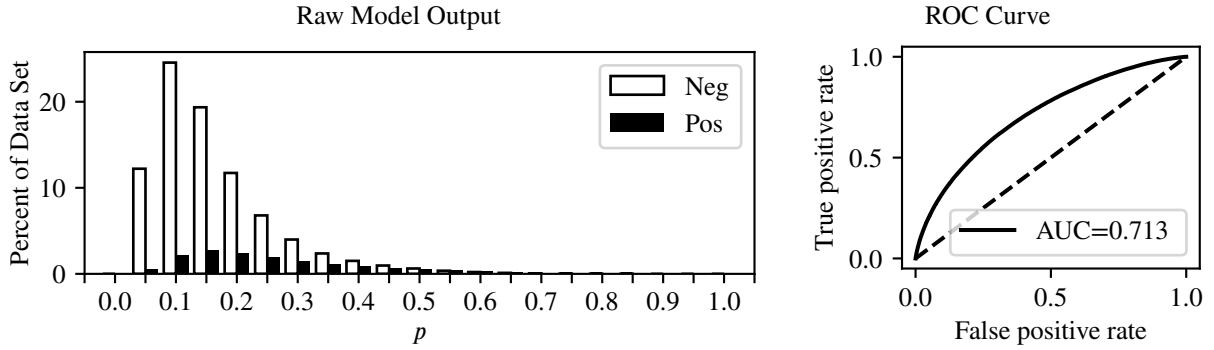
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	6,057	840	0.12	6,057	599,553	840	107,116	0.15	0.99	5.55	0.99
0.05	3,916	518	0.12	9,973	595,637	1,358	106,598	0.15	0.99	5.52	0.98
0.10	5,431	765	0.12	15,404	590,206	2,123	105,833	0.15	0.98	5.47	0.98
0.15	6,990	993	0.12	22,394	583,216	3,116	104,840	0.15	0.97	5.40	0.96
0.20	8,951	1,282	0.13	31,345	574,265	4,398	103,558	0.15	0.96	5.32	0.95
0.25	10,702	1,530	0.13	42,047	563,563	5,928	102,028	0.15	0.95	5.22	0.93
0.30	11,243	1,740	0.13	53,290	552,320	7,668	100,288	0.15	0.93	5.12	0.91
0.35	11,306	1,721	0.13	64,596	541,014	9,389	98,567	0.15	0.91	5.01	0.90
0.40	11,066	1,797	0.14	75,662	529,948	11,186	96,770	0.15	0.90	4.91	0.88
0.45	9,834	1,761	0.15	85,496	520,114	12,947	95,009	0.15	0.88	4.82	0.86
0.50	9,331	1,609	0.15	94,827	510,783	14,556	93,400	0.15	0.87	4.73	0.85
0.55	64,293	3,872	0.06	159,120	446,490	18,428	89,528	0.17	0.83	4.14	0.75
0.60	196,980	19,669	0.09	356,100	249,510	38,097	69,859	0.22	0.65	2.31	0.45
0.65	185,936	39,149	0.17	542,036	63,574	77,246	30,710	0.33	0.28	0.59	0.13
0.70	45,021	19,992	0.31	587,057	18,553	97,238	10,718	0.37	0.10	0.17	0.04
0.75	10,023	7,550	0.43	597,080	8,530	104,788	3,168	0.27	0.03	0.08	0.02
0.80	1,647	784	0.32	598,727	6,883	105,572	2,384	0.26	0.02	0.06	0.01
0.85	1,145	329	0.22	599,872	5,738	105,901	2,055	0.26	0.02	0.05	0.01
0.90	1,144	334	0.23	601,016	4,594	106,235	1,721	0.27	0.02	0.04	0.01
0.95	954	359	0.27	601,970	3,640	106,594	1,362	0.27	0.01	0.03	0.01
1.00	3,640	1,362	0.27	605,610	0	107,956	0	nan	0.00	0.00	0.00

RUSBoost\_5\_Fold\_Medium\_Test\_Transformed\_95



$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	15,142	2,094	0.12	15,142	590,468	2,094	105,862	0.15	0.98	5.47	0.98
0.05	4,437	646	0.13	19,579	586,031	2,740	105,216	0.15	0.97	5.43	0.97
0.10	5,280	761	0.13	24,859	580,751	3,501	104,455	0.15	0.97	5.38	0.96
0.15	6,118	852	0.12	30,977	574,633	4,353	103,603	0.15	0.96	5.32	0.95
0.20	7,071	981	0.12	38,048	567,562	5,334	102,622	0.15	0.95	5.26	0.94
0.25	7,348	1,095	0.13	45,396	560,214	6,429	101,527	0.15	0.94	5.19	0.93
0.30	7,596	1,198	0.14	52,992	552,618	7,627	100,329	0.15	0.93	5.12	0.92
0.35	7,597	1,139	0.13	60,589	545,021	8,766	99,190	0.15	0.92	5.05	0.90
0.40	7,532	1,170	0.13	68,121	537,489	9,936	98,020	0.15	0.91	4.98	0.89
0.45	7,350	1,217	0.14	75,471	530,139	11,153	96,803	0.15	0.90	4.91	0.88
0.50	6,944	1,186	0.15	82,415	523,195	12,339	95,617	0.15	0.89	4.85	0.87
0.55	5,830	1,129	0.16	88,245	517,365	13,468	94,488	0.15	0.88	4.79	0.86
0.60	6,433	1,071	0.14	94,678	510,932	14,539	93,417	0.15	0.87	4.73	0.85
0.65	28,370	1,694	0.06	123,048	482,562	16,233	91,723	0.16	0.85	4.47	0.80
0.70	85,277	5,725	0.06	208,325	397,285	21,958	85,998	0.18	0.80	3.68	0.68
0.75	146,727	15,998	0.10	355,052	250,558	37,956	70,000	0.22	0.65	2.32	0.45
0.80	144,835	27,256	0.16	499,887	105,723	65,212	42,744	0.29	0.40	0.98	0.21
0.85	66,056	20,851	0.24	565,943	39,667	86,063	21,893	0.36	0.20	0.37	0.09
0.90	21,189	11,212	0.35	587,132	18,478	97,275	10,681	0.37	0.10	0.17	0.04
0.95	8,398	6,389	0.43	595,530	10,080	103,664	4,292	0.30	0.04	0.09	0.02
1.00	10,080	4,292	0.30	605,610	0	107,956	0	nan	0.00	0.00	0.00

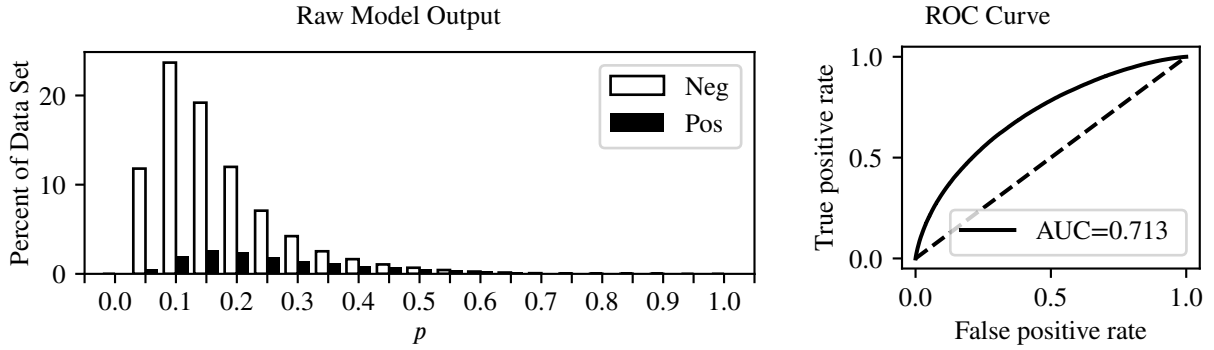
KBFC\_5\_Fold\_alpha\_0\_5\_gamma\_0\_0\_Medium\_Test



	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
p											
0.00	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.05	87,170	3,517	0.04	87,170	518,440	3,517	104,439	0.17	0.97	4.80	0.87
0.10	175,179	15,047	0.08	262,349	343,261	18,564	89,392	0.21	0.83	3.18	0.61
0.15	138,123	19,572	0.12	400,472	205,138	38,136	69,820	0.25	0.65	1.90	0.39
0.20	83,669	17,200	0.17	484,141	121,469	55,336	52,620	0.30	0.49	1.13	0.24
0.25	48,461	13,427	0.22	532,602	73,008	68,763	39,193	0.35	0.36	0.68	0.16
0.30	28,456	10,335	0.27	561,058	44,552	79,098	28,858	0.39	0.27	0.41	0.10
0.35	16,924	7,856	0.32	577,982	27,628	86,954	21,002	0.43	0.19	0.26	0.07
0.40	10,769	6,164	0.36	588,751	16,859	93,118	14,838	0.47	0.14	0.16	0.04
0.45	6,904	4,749	0.41	595,655	9,955	97,867	10,089	0.50	0.09	0.09	0.03
0.50	4,438	3,644	0.45	600,093	5,517	101,511	6,445	0.54	0.06	0.05	0.02
0.55	2,597	2,697	0.51	602,690	2,920	104,208	3,748	0.56	0.03	0.03	0.01
0.60	1,512	1,734	0.53	604,202	1,408	105,942	2,014	0.59	0.02	0.01	0.00
0.65	815	1,082	0.57	605,017	593	107,024	932	0.61	0.01	0.01	0.00
0.70	384	586	0.60	605,401	209	107,610	346	0.62	0.00	0.00	0.00
0.75	147	219	0.60	605,548	62	107,829	127	0.67	0.00	0.00	0.00
0.80	47	89	0.65	605,595	15	107,918	38	0.72	0.00	0.00	0.00
0.85	15	34	0.69	605,610	0	107,952	4	1.00	0.00	0.00	0.00
0.90	0	3	1.00	605,610	0	107,955	1	1.00	0.00	0.00	0.00
0.95	0	0	nan	605,610	0	107,955	1	1.00	0.00	0.00	0.00
1.00	0	1	1.00	605,610	0	107,956	0	nan	0.00	0.00	0.00

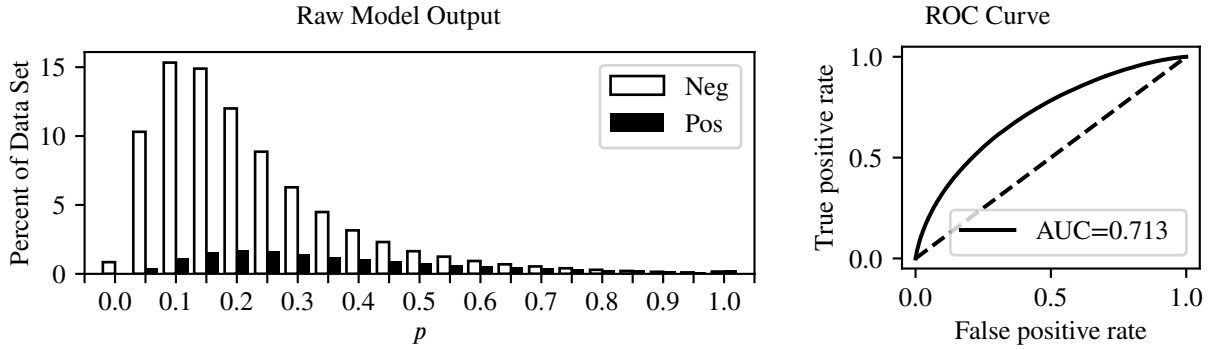


KBFC\_5\_Fold\_alpha\_0\_5\_gamma\_0\_0\_Medium\_Test\_Transformed\_100



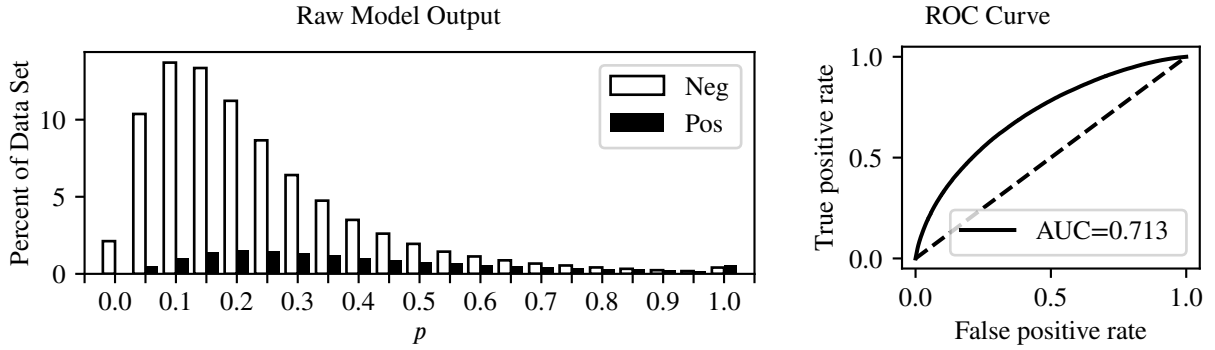
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	1	0	0.00	1	605,609	0	107,956	0.15	1.00	5.61	1.00
0.05	84,210	3,329	0.04	84,211	521,399	3,329	104,627	0.17	0.97	4.83	0.88
0.10	169,026	14,301	0.08	253,237	352,373	17,630	90,326	0.20	0.84	3.26	0.62
0.15	136,960	18,673	0.12	390,197	215,413	36,303	71,653	0.25	0.66	2.00	0.40
0.20	85,585	17,036	0.17	475,782	129,828	53,339	54,617	0.30	0.51	1.20	0.26
0.25	50,551	13,512	0.21	526,333	79,277	66,851	41,105	0.34	0.38	0.73	0.17
0.30	30,171	10,398	0.26	556,504	49,106	77,249	30,707	0.38	0.28	0.45	0.11
0.35	18,066	8,023	0.31	574,570	31,040	85,272	22,684	0.42	0.21	0.29	0.08
0.40	11,753	6,336	0.35	586,323	19,287	91,608	16,348	0.46	0.15	0.18	0.05
0.45	7,554	4,901	0.39	593,877	11,733	96,509	11,447	0.49	0.11	0.11	0.03
0.50	4,890	3,816	0.44	598,767	6,843	100,325	7,631	0.53	0.07	0.06	0.02
0.55	3,060	2,991	0.49	601,827	3,783	103,316	4,640	0.55	0.04	0.04	0.01
0.60	1,841	1,971	0.52	603,668	1,942	105,287	2,669	0.58	0.02	0.02	0.01
0.65	1,057	1,323	0.56	604,725	885	106,610	1,346	0.60	0.01	0.01	0.00
0.70	533	742	0.58	605,258	352	107,352	604	0.63	0.01	0.00	0.00
0.75	236	381	0.62	605,494	116	107,733	223	0.66	0.00	0.00	0.00
0.80	76	147	0.66	605,570	40	107,880	76	0.66	0.00	0.00	0.00
0.85	31	56	0.64	605,601	9	107,936	20	0.69	0.00	0.00	0.00
0.90	9	18	0.67	605,610	0	107,954	2	1.00	0.00	0.00	0.00
0.95	0	1	1.00	605,610	0	107,955	1	1.00	0.00	0.00	0.00
1.00	0	1	1.00	605,610	0	107,956	0	nan	0.00	0.00	0.00

KBFC\_5\_Fold\_alpha\_0\_5\_gamma\_0\_0\_Medium\_Test\_Transformed\_98



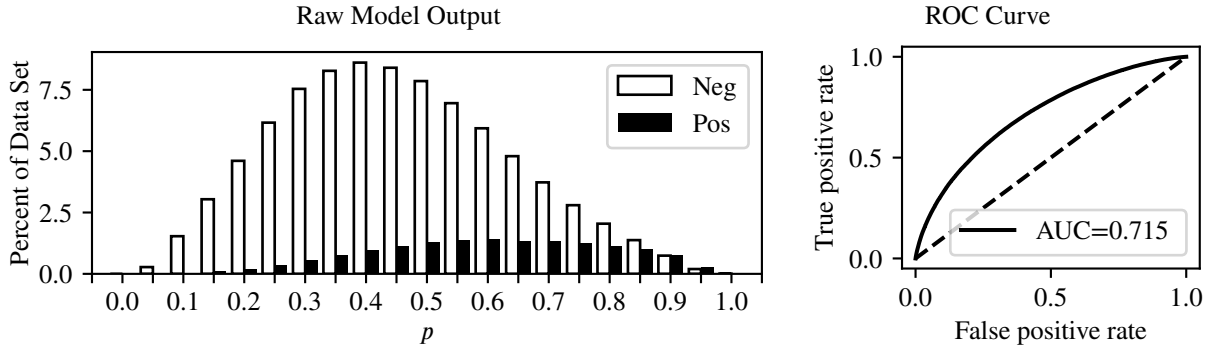
p	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	6,057	115	0.02	6,057	599,553	115	107,841	0.15	1.00	5.55	0.99
0.05	73,565	2,974	0.04	79,622	525,988	3,089	104,867	0.17	0.97	4.87	0.88
0.10	109,399	7,994	0.07	189,021	416,589	11,083	96,873	0.19	0.90	3.86	0.72
0.15	106,282	11,325	0.10	295,303	310,307	22,408	85,548	0.22	0.79	2.87	0.55
0.20	85,657	12,319	0.13	380,960	224,650	34,727	73,229	0.25	0.68	2.08	0.42
0.25	63,260	11,558	0.15	444,220	161,390	46,285	61,671	0.28	0.57	1.49	0.31
0.30	44,818	10,290	0.19	489,038	116,572	56,575	51,381	0.31	0.48	1.08	0.24
0.35	32,012	8,575	0.21	521,050	84,560	65,150	42,806	0.34	0.40	0.78	0.18
0.40	22,513	7,297	0.24	543,563	62,047	72,447	35,509	0.36	0.33	0.57	0.14
0.45	16,487	6,264	0.28	560,050	45,560	78,711	29,245	0.39	0.27	0.42	0.10
0.50	11,720	5,240	0.31	571,770	33,840	83,951	24,005	0.41	0.22	0.31	0.08
0.55	8,911	4,382	0.33	580,681	24,929	88,333	19,623	0.44	0.18	0.23	0.06
0.60	6,657	3,883	0.37	587,338	18,272	92,216	15,740	0.46	0.15	0.17	0.05
0.65	4,936	3,224	0.40	592,274	13,336	95,440	12,516	0.48	0.12	0.12	0.04
0.70	3,845	2,740	0.42	596,119	9,491	98,180	9,776	0.51	0.09	0.09	0.03
0.75	2,885	2,367	0.45	599,004	6,606	100,547	7,409	0.53	0.07	0.06	0.02
0.80	2,100	1,990	0.49	601,104	4,506	102,537	5,419	0.55	0.05	0.04	0.01
0.85	1,503	1,570	0.51	602,607	3,003	104,107	3,849	0.56	0.04	0.03	0.01
0.90	1,063	1,193	0.53	603,670	1,940	105,300	2,656	0.58	0.02	0.02	0.01
0.95	743	946	0.56	604,413	1,197	106,246	1,710	0.59	0.02	0.01	0.00
1.00	1,197	1,710	0.59	605,610	0	107,956	0	nan	0.00	0.00	0.00

KBFC\_5\_Fold\_alpha\_0\_5\_gamma\_0\_0\_Medium\_Test\_Transformed\_95



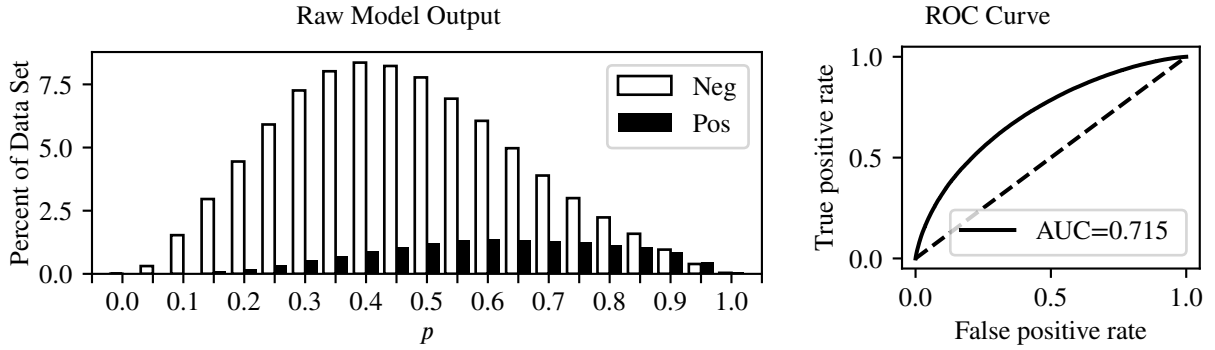
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	15,141	353	0.02	15,141	590,469	353	107,603	0.15	1.00	5.47	0.98
0.05	74,004	3,272	0.04	89,145	516,465	3,625	104,331	0.17	0.97	4.78	0.87
0.10	97,782	7,303	0.07	186,927	418,683	10,928	97,028	0.19	0.90	3.88	0.72
0.15	95,273	9,877	0.09	282,200	323,410	20,805	87,151	0.21	0.81	3.00	0.58
0.20	80,087	10,913	0.12	362,287	243,323	31,718	76,238	0.24	0.71	2.25	0.45
0.25	61,809	10,580	0.15	424,096	181,514	42,298	65,658	0.27	0.61	1.68	0.35
0.30	45,730	9,650	0.17	469,826	135,784	51,948	56,008	0.29	0.52	1.26	0.27
0.35	33,883	8,396	0.20	503,709	101,901	60,344	47,612	0.32	0.44	0.94	0.21
0.40	24,980	7,223	0.22	528,689	76,921	67,567	40,389	0.34	0.37	0.71	0.16
0.45	18,616	6,205	0.25	547,305	58,305	73,772	34,184	0.37	0.32	0.54	0.13
0.50	13,879	5,366	0.28	561,184	44,426	79,138	28,818	0.39	0.27	0.41	0.10
0.55	10,282	4,648	0.31	571,466	34,144	83,786	24,170	0.41	0.22	0.32	0.08
0.60	8,053	3,971	0.33	579,519	26,091	87,757	20,199	0.44	0.19	0.24	0.06
0.65	6,260	3,551	0.36	585,779	19,831	91,308	16,648	0.46	0.15	0.18	0.05
0.70	4,762	2,971	0.38	590,541	15,069	94,279	13,677	0.48	0.13	0.14	0.04
0.75	3,879	2,606	0.40	594,420	11,190	96,885	11,071	0.50	0.10	0.10	0.03
0.80	2,971	2,276	0.43	597,391	8,219	99,161	8,795	0.52	0.08	0.08	0.02
0.85	2,331	2,003	0.46	599,722	5,888	101,164	6,792	0.54	0.06	0.05	0.02
0.90	1,692	1,691	0.50	601,414	4,196	102,855	5,101	0.55	0.05	0.04	0.01
0.95	1,276	1,353	0.51	602,690	2,920	104,208	3,748	0.56	0.03	0.03	0.01
1.00	2,920	3,748	0.56	605,610	0	107,956	0	nan	0.00	0.00	0.00

KBFC\_5\_Fold\_alpha\_balanced\_gamma\_0\_0\_Medium\_Test



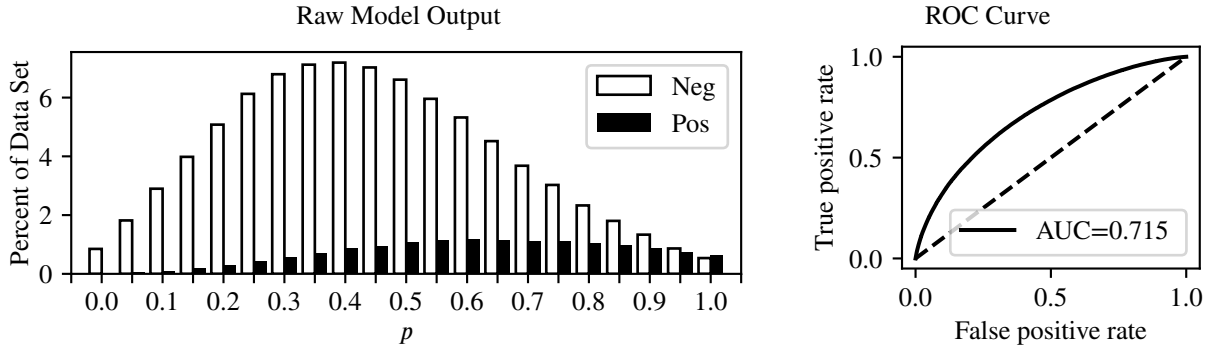
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.05	1,969	25	0.01	1,969	603,641	25	107,931	0.15	1.00	5.59	1.00
0.10	10,947	232	0.02	12,916	592,694	257	107,699	0.15	1.00	5.49	0.98
0.15	21,693	695	0.03	34,609	571,001	952	107,004	0.16	0.99	5.29	0.95
0.20	32,868	1,440	0.04	67,477	538,133	2,392	105,564	0.16	0.98	4.98	0.90
0.25	43,974	2,495	0.05	111,451	494,159	4,887	103,069	0.17	0.95	4.58	0.84
0.30	53,791	3,987	0.07	165,242	440,368	8,874	99,082	0.18	0.92	4.08	0.76
0.35	59,041	5,347	0.08	224,283	381,327	14,221	93,735	0.20	0.87	3.53	0.67
0.40	61,435	6,756	0.10	285,718	319,892	20,977	86,979	0.21	0.81	2.96	0.57
0.45	59,936	8,014	0.12	345,654	259,956	28,991	78,965	0.23	0.73	2.41	0.47
0.50	56,060	9,084	0.14	401,714	203,896	38,075	69,881	0.26	0.65	1.89	0.38
0.55	49,635	9,645	0.16	451,349	154,261	47,720	60,236	0.28	0.56	1.43	0.30
0.60	42,331	9,952	0.19	493,680	111,930	57,672	50,284	0.31	0.47	1.04	0.23
0.65	34,222	9,494	0.22	527,902	77,708	67,166	40,790	0.34	0.38	0.72	0.17
0.70	26,604	9,400	0.26	554,506	51,104	76,566	31,390	0.38	0.29	0.47	0.12
0.75	19,969	8,811	0.31	574,475	31,135	85,377	22,579	0.42	0.21	0.29	0.08
0.80	14,589	8,097	0.36	589,064	16,546	93,474	14,482	0.47	0.13	0.15	0.04
0.85	9,812	7,193	0.42	598,876	6,734	100,667	7,289	0.52	0.07	0.06	0.02
0.90	5,298	5,270	0.50	604,174	1,436	105,937	2,019	0.58	0.02	0.01	0.00
0.95	1,400	1,931	0.58	605,574	36	107,868	88	0.71	0.00	0.00	0.00
1.00	36	88	0.71	605,610	0	107,956	0	nan	0.00	0.00	0.00

KBFC\_5\_Fold\_alpha\_balanced\_gamma\_0\_0\_Medium\_Test\_Transformed\_100



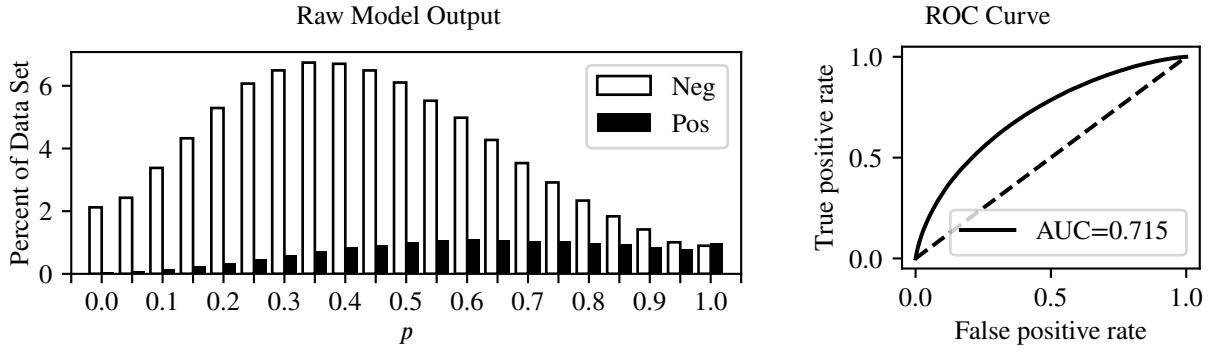
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	1	0	0.00	1	605,609	0	107,956	0.15	1.00	5.61	1.00
0.05	2,200	29	0.01	2,201	603,409	29	107,927	0.15	1.00	5.59	1.00
0.10	10,928	236	0.02	13,129	592,481	265	107,691	0.15	1.00	5.49	0.98
0.15	21,133	675	0.03	34,262	571,348	940	107,016	0.16	0.99	5.29	0.95
0.20	31,733	1,373	0.04	65,995	539,615	2,313	105,643	0.16	0.98	5.00	0.90
0.25	42,190	2,374	0.05	108,185	497,425	4,687	103,269	0.17	0.96	4.61	0.84
0.30	51,803	3,762	0.07	159,988	445,622	8,449	99,507	0.18	0.92	4.13	0.76
0.35	57,222	5,020	0.08	217,210	388,400	13,469	94,487	0.20	0.88	3.60	0.68
0.40	59,670	6,479	0.10	276,880	328,730	19,948	88,008	0.21	0.82	3.05	0.58
0.45	58,713	7,602	0.11	335,593	270,017	27,550	80,406	0.23	0.74	2.50	0.49
0.50	55,484	8,613	0.13	391,077	214,533	36,163	71,793	0.25	0.67	1.99	0.40
0.55	49,479	9,378	0.16	440,556	165,054	45,541	62,415	0.27	0.58	1.53	0.32
0.60	43,219	9,690	0.18	483,775	121,835	55,231	52,725	0.30	0.49	1.13	0.24
0.65	35,487	9,404	0.21	519,262	86,348	64,635	43,321	0.33	0.40	0.80	0.18
0.70	27,773	9,152	0.25	547,035	58,575	73,787	34,169	0.37	0.32	0.54	0.13
0.75	21,392	8,759	0.29	568,427	37,183	82,546	25,410	0.41	0.24	0.34	0.09
0.80	15,943	8,170	0.34	584,370	21,240	90,716	17,240	0.45	0.16	0.20	0.05
0.85	11,324	7,361	0.39	595,694	9,916	98,077	9,879	0.50	0.09	0.09	0.03
0.90	6,846	6,017	0.47	602,540	3,070	104,094	3,862	0.56	0.04	0.03	0.01
0.95	2,787	3,349	0.55	605,327	283	107,443	513	0.64	0.00	0.00	0.00
1.00	283	513	0.64	605,610	0	107,956	0	nan	0.00	0.00	0.00

KBFC\_5\_Fold\_alpha\_balanced\_gamma\_0\_0\_Medium\_Test\_Transformed\_98



$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	6,058	105	0.02	6,058	599,552	105	107,851	0.15	1.00	5.55	0.99
0.05	12,976	318	0.02	19,034	586,576	423	107,533	0.15	1.00	5.43	0.97
0.10	20,681	718	0.03	39,715	565,895	1,141	106,815	0.16	0.99	5.24	0.94
0.15	28,419	1,282	0.04	68,134	537,476	2,423	105,533	0.16	0.98	4.98	0.90
0.20	36,245	2,019	0.05	104,379	501,231	4,442	103,514	0.17	0.96	4.64	0.85
0.25	43,720	3,066	0.07	148,099	457,511	7,508	100,448	0.18	0.93	4.24	0.78
0.30	48,489	4,050	0.08	196,588	409,022	11,558	96,398	0.19	0.89	3.79	0.71
0.35	50,810	5,016	0.09	247,398	358,212	16,574	91,382	0.20	0.85	3.32	0.63
0.40	51,313	6,076	0.11	298,711	306,899	22,650	85,306	0.22	0.79	2.84	0.55
0.45	50,133	6,798	0.12	348,844	256,766	29,448	78,508	0.23	0.73	2.38	0.47
0.50	47,169	7,594	0.14	396,013	209,597	37,042	70,914	0.25	0.66	1.94	0.39
0.55	42,512	8,042	0.16	438,525	167,085	45,084	62,872	0.27	0.58	1.55	0.32
0.60	37,985	8,322	0.18	476,510	129,100	53,406	54,550	0.30	0.51	1.20	0.26
0.65	32,239	8,186	0.20	508,749	96,861	61,592	46,364	0.32	0.43	0.90	0.20
0.70	26,260	7,905	0.23	535,009	70,601	69,497	38,459	0.35	0.36	0.65	0.15
0.75	21,596	7,901	0.27	556,605	49,005	77,398	30,558	0.38	0.28	0.45	0.11
0.80	16,619	7,371	0.31	573,224	32,386	84,769	23,187	0.42	0.21	0.30	0.08
0.85	12,866	6,942	0.35	586,090	19,520	91,711	16,245	0.45	0.15	0.18	0.05
0.90	9,521	6,306	0.40	595,611	9,999	98,017	9,939	0.50	0.09	0.09	0.03
0.95	6,166	5,325	0.46	601,777	3,833	103,342	4,614	0.55	0.04	0.04	0.01
1.00	3,833	4,614	0.55	605,610	0	107,956	0	nan	0.00	0.00	0.00

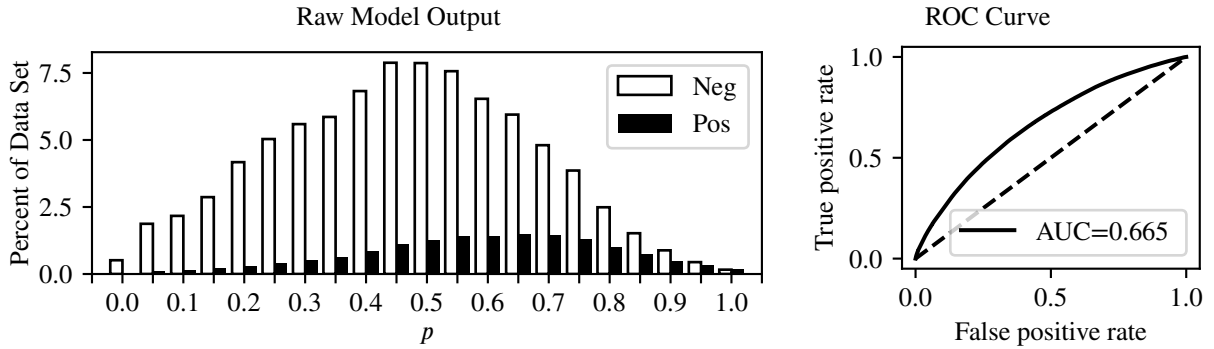
KBFC\_5\_Fold\_alpha\_balanced\_gamma\_0\_0\_Medium\_Test\_Transformed\_95



$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	15,141	318	0.02	15,141	590,469	318	107,638	0.15	1.00	5.47	0.98
0.05	17,324	545	0.03	32,465	573,145	863	107,093	0.16	0.99	5.31	0.95
0.10	24,119	977	0.04	56,584	549,026	1,840	106,116	0.16	0.98	5.09	0.92
0.15	30,867	1,623	0.05	87,451	518,159	3,463	104,493	0.17	0.97	4.80	0.87
0.20	37,760	2,366	0.06	125,211	480,399	5,829	102,127	0.18	0.95	4.45	0.82
0.25	43,320	3,292	0.07	168,531	437,079	9,121	98,835	0.18	0.92	4.05	0.75
0.30	46,322	4,132	0.08	214,853	390,757	13,253	94,703	0.20	0.88	3.62	0.68
0.35	48,099	5,012	0.09	262,952	342,658	18,265	89,691	0.21	0.83	3.17	0.61
0.40	47,824	5,921	0.11	310,776	294,834	24,186	83,770	0.22	0.78	2.73	0.53
0.45	46,314	6,503	0.12	357,090	248,520	30,689	77,267	0.24	0.72	2.30	0.46
0.50	43,566	7,200	0.14	400,656	204,954	37,889	70,067	0.25	0.65	1.90	0.39
0.55	39,411	7,555	0.16	440,067	165,543	45,444	62,512	0.27	0.58	1.53	0.32
0.60	35,548	7,771	0.18	475,615	129,995	53,215	54,741	0.30	0.51	1.20	0.26
0.65	30,485	7,643	0.20	506,100	99,510	60,858	47,098	0.32	0.44	0.92	0.21
0.70	25,221	7,381	0.23	531,321	74,289	68,239	39,717	0.35	0.37	0.69	0.16
0.75	20,807	7,512	0.27	552,128	53,482	75,751	32,205	0.38	0.30	0.50	0.12
0.80	16,681	6,957	0.29	568,809	36,801	82,708	25,248	0.41	0.23	0.34	0.09
0.85	13,103	6,603	0.34	581,912	23,698	89,311	18,645	0.44	0.17	0.22	0.06
0.90	10,112	6,055	0.37	592,024	13,586	95,366	12,590	0.48	0.12	0.13	0.04
0.95	7,188	5,602	0.44	599,212	6,398	100,968	6,988	0.52	0.06	0.06	0.02
1.00	6,398	6,988	0.52	605,610	0	107,956	0	nan	0.00	0.00	0.00

## 16.4. Easy Features

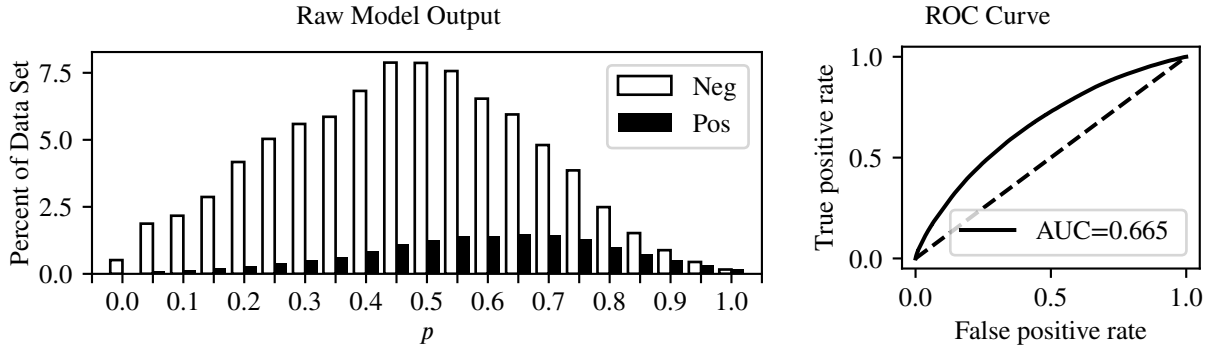
BRFC\_5\_Fold\_alpha\_0\_5\_Easy\_Test



	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
p											
0.00	3,667	129	0.03	3,667	601,943	129	107,827	0.15	1.00	5.58	0.99
0.05	13,368	781	0.06	17,035	588,575	910	107,046	0.15	0.99	5.45	0.97
0.10	15,474	878	0.05	32,509	573,101	1,788	106,168	0.16	0.98	5.31	0.95
0.15	20,464	1,353	0.06	52,973	552,637	3,141	104,815	0.16	0.97	5.12	0.92
0.20	29,774	2,057	0.06	82,747	522,863	5,198	102,758	0.16	0.95	4.84	0.88
0.25	35,927	2,805	0.07	118,674	486,936	8,003	99,953	0.17	0.93	4.51	0.82
0.30	39,902	3,558	0.08	158,576	447,034	11,561	96,395	0.18	0.89	4.14	0.76
0.35	41,811	4,288	0.09	200,387	405,223	15,849	92,107	0.19	0.85	3.75	0.70
0.40	48,697	6,092	0.11	249,084	356,526	21,941	86,015	0.19	0.80	3.30	0.62
0.45	56,236	7,756	0.12	305,320	300,290	29,697	78,259	0.21	0.72	2.78	0.53
0.50	56,151	8,847	0.14	361,471	244,139	38,544	69,412	0.22	0.64	2.26	0.44
0.55	53,989	10,054	0.16	415,460	190,150	48,598	59,358	0.24	0.55	1.76	0.35
0.60	46,637	9,953	0.18	462,097	143,513	58,551	49,405	0.26	0.46	1.33	0.27
0.65	42,436	10,619	0.20	504,533	101,077	69,170	38,786	0.28	0.36	0.94	0.20
0.70	34,290	10,367	0.23	538,823	66,787	79,537	28,419	0.30	0.26	0.62	0.13
0.75	27,545	9,286	0.25	566,368	39,242	88,823	19,133	0.33	0.18	0.36	0.08
0.80	17,766	7,085	0.29	584,134	21,476	95,908	12,048	0.36	0.11	0.20	0.05
0.85	10,855	5,113	0.32	594,989	10,621	101,021	6,935	0.40	0.06	0.10	0.02
0.90	6,302	3,466	0.35	601,291	4,319	104,487	3,469	0.45	0.03	0.04	0.01
0.95	3,163	2,267	0.42	604,454	1,156	106,754	1,202	0.51	0.01	0.01	0.00
1.00	1,156	1,202	0.51	605,610	0	107,956	0	nan	0.00	0.00	0.00

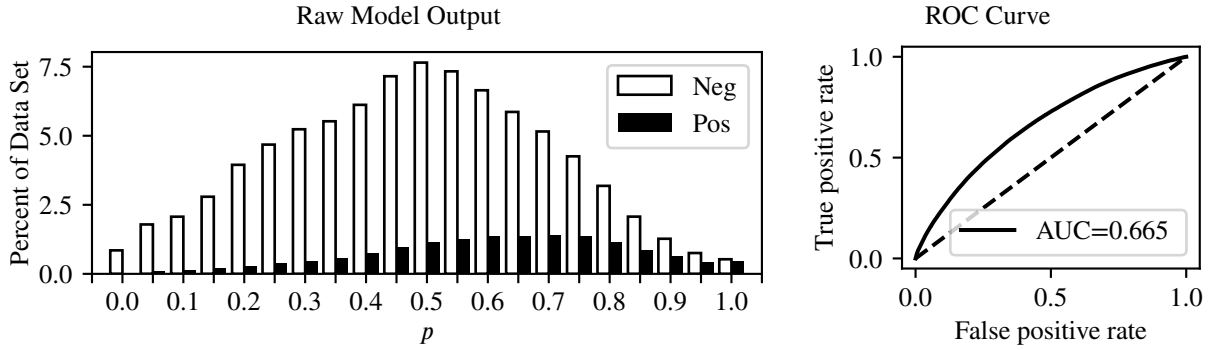


BRFC\_5\_Fold\_alpha\_0\_5\_Easy\_Test\_Transformed\_100



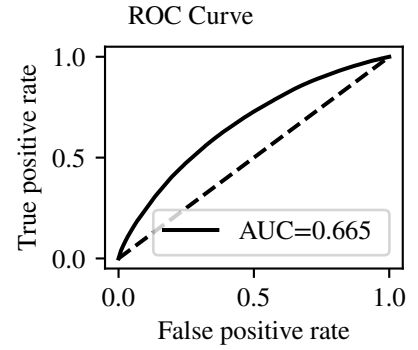
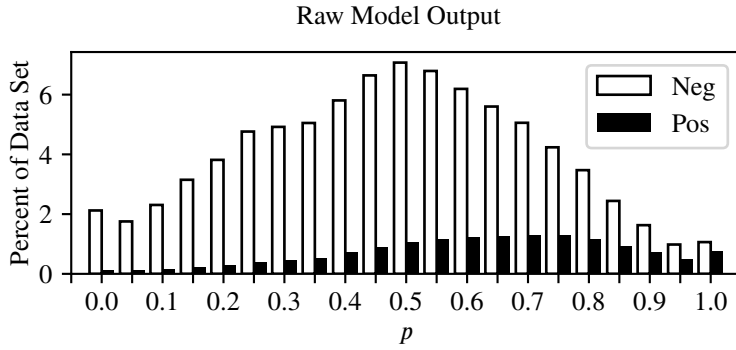
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	3,667	129	0.03	3,667	601,943	129	107,827	0.15	1.00	5.58	0.99
0.05	13,368	781	0.06	17,035	588,575	910	107,046	0.15	0.99	5.45	0.97
0.10	15,474	878	0.05	32,509	573,101	1,788	106,168	0.16	0.98	5.31	0.95
0.15	20,464	1,353	0.06	52,973	552,637	3,141	104,815	0.16	0.97	5.12	0.92
0.20	29,774	2,057	0.06	82,747	522,863	5,198	102,758	0.16	0.95	4.84	0.88
0.25	35,927	2,805	0.07	118,674	486,936	8,003	99,953	0.17	0.93	4.51	0.82
0.30	39,902	3,558	0.08	158,576	447,034	11,561	96,395	0.18	0.89	4.14	0.76
0.35	41,811	4,288	0.09	200,387	405,223	15,849	92,107	0.19	0.85	3.75	0.70
0.40	48,697	6,092	0.11	249,084	356,526	21,941	86,015	0.19	0.80	3.30	0.62
0.45	56,236	7,756	0.12	305,320	300,290	29,697	78,259	0.21	0.72	2.78	0.53
0.50	56,151	8,847	0.14	361,471	244,139	38,544	69,412	0.22	0.64	2.26	0.44
0.55	53,989	10,054	0.16	415,460	190,150	48,598	59,358	0.24	0.55	1.76	0.35
0.60	46,637	9,953	0.18	462,097	143,513	58,551	49,405	0.26	0.46	1.33	0.27
0.65	42,436	10,619	0.20	504,533	101,077	69,170	38,786	0.28	0.36	0.94	0.20
0.70	34,290	10,367	0.23	538,823	66,787	79,537	28,419	0.30	0.26	0.62	0.13
0.75	27,545	9,286	0.25	566,368	39,242	88,823	19,133	0.33	0.18	0.36	0.08
0.80	17,766	7,085	0.29	584,134	21,476	95,908	12,048	0.36	0.11	0.20	0.05
0.85	10,855	5,113	0.32	594,989	10,621	101,021	6,935	0.40	0.06	0.10	0.02
0.90	6,302	3,466	0.35	601,291	4,319	104,487	3,469	0.45	0.03	0.04	0.01
0.95	3,163	2,267	0.42	604,454	1,156	106,754	1,202	0.51	0.01	0.01	0.00
1.00	1,156	1,202	0.51	605,610	0	107,956	0	nan	0.00	0.00	0.00

BRFC\_5\_Fold\_alpha\_0\_5\_Easy\_Test\_Transformed\_98



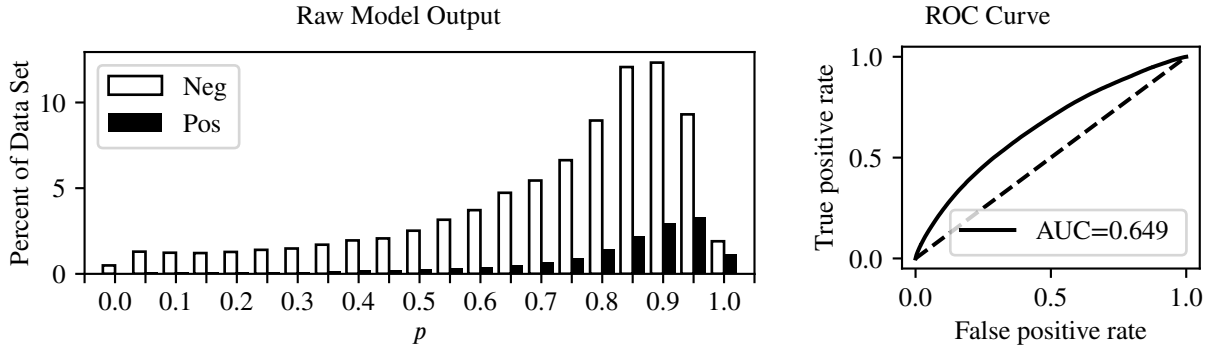
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	6,069	257	0.04	6,069	599,541	257	107,699	0.15	1.00	5.55	0.99
0.05	12,763	759	0.06	18,832	586,778	1,016	106,940	0.15	0.99	5.44	0.97
0.10	14,766	835	0.05	33,598	572,012	1,851	106,105	0.16	0.98	5.30	0.95
0.15	19,927	1,329	0.06	53,525	552,085	3,180	104,776	0.16	0.97	5.11	0.92
0.20	28,169	1,950	0.06	81,694	523,916	5,130	102,826	0.16	0.95	4.85	0.88
0.25	33,392	2,609	0.07	115,086	490,524	7,739	100,217	0.17	0.93	4.54	0.83
0.30	37,355	3,279	0.08	152,441	453,169	11,018	96,938	0.18	0.90	4.20	0.77
0.35	39,417	3,891	0.09	191,858	413,752	14,909	93,047	0.18	0.86	3.83	0.71
0.40	43,663	5,285	0.11	235,521	370,089	20,194	87,762	0.19	0.81	3.43	0.64
0.45	51,051	6,884	0.12	286,572	319,038	27,078	80,878	0.20	0.75	2.96	0.56
0.50	54,578	8,149	0.13	341,150	264,460	35,227	72,729	0.22	0.67	2.45	0.47
0.55	52,317	8,981	0.15	393,467	212,143	44,208	63,748	0.23	0.59	1.97	0.39
0.60	47,428	9,606	0.17	440,895	164,715	53,814	54,142	0.25	0.50	1.53	0.31
0.65	41,831	9,578	0.19	482,726	122,884	63,392	44,564	0.27	0.41	1.14	0.23
0.70	36,785	10,037	0.21	519,511	86,099	73,429	34,527	0.29	0.32	0.80	0.17
0.75	30,362	9,661	0.24	549,873	55,737	83,090	24,866	0.31	0.23	0.52	0.11
0.80	22,733	8,101	0.26	572,606	33,004	91,191	16,765	0.34	0.16	0.31	0.07
0.85	14,785	6,126	0.29	587,391	18,219	97,317	10,639	0.37	0.10	0.17	0.04
0.90	9,067	4,458	0.33	596,458	9,152	101,775	6,181	0.40	0.06	0.08	0.02
0.95	5,383	3,062	0.36	601,841	3,769	104,837	3,119	0.45	0.03	0.03	0.01
1.00	3,769	3,119	0.45	605,610	0	107,956	0	nan	0.00	0.00	0.00

BRFC\_5\_Fold\_alpha\_0\_5\_Easy\_Test\_Transformed\_95



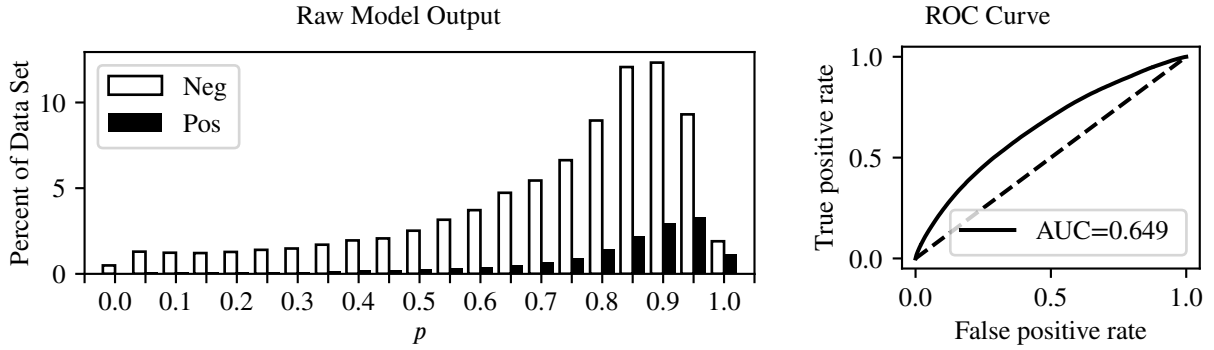
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	15,142	810	0.05	15,142	590,468	810	107,146	0.15	0.99	5.47	0.98
0.05	12,522	753	0.06	27,664	577,946	1,563	106,393	0.16	0.99	5.35	0.96
0.10	16,459	969	0.06	44,123	561,487	2,532	105,424	0.16	0.98	5.20	0.93
0.15	22,472	1,554	0.06	66,595	539,015	4,086	103,870	0.16	0.96	4.99	0.90
0.20	27,228	1,968	0.07	93,823	511,787	6,054	101,902	0.17	0.94	4.74	0.86
0.25	33,993	2,730	0.07	127,816	477,794	8,784	99,172	0.17	0.92	4.43	0.81
0.30	35,106	3,230	0.08	162,922	442,688	12,014	95,942	0.18	0.89	4.10	0.75
0.35	36,040	3,689	0.09	198,962	406,648	15,703	92,253	0.18	0.85	3.77	0.70
0.40	41,429	5,147	0.11	240,391	365,219	20,850	87,106	0.19	0.81	3.38	0.63
0.45	47,407	6,423	0.12	287,798	317,812	27,273	80,683	0.20	0.75	2.94	0.56
0.50	50,465	7,443	0.13	338,263	267,347	34,716	73,240	0.22	0.68	2.48	0.48
0.55	48,465	8,277	0.15	386,728	218,882	42,993	64,963	0.23	0.60	2.03	0.40
0.60	44,183	8,691	0.16	430,911	174,699	51,684	56,272	0.24	0.52	1.62	0.32
0.65	39,968	8,867	0.18	470,879	134,731	60,551	47,405	0.26	0.44	1.25	0.26
0.70	36,085	9,284	0.20	506,964	98,646	69,835	38,121	0.28	0.35	0.91	0.19
0.75	30,230	9,209	0.23	537,194	68,416	79,044	28,912	0.30	0.27	0.63	0.14
0.80	24,772	8,188	0.25	561,966	43,644	87,232	20,724	0.32	0.19	0.40	0.09
0.85	17,423	6,671	0.28	579,389	26,221	93,903	14,053	0.35	0.13	0.24	0.06
0.90	11,630	5,123	0.31	591,019	14,591	99,026	8,930	0.38	0.08	0.14	0.03
0.95	7,006	3,572	0.34	598,025	7,585	102,598	5,358	0.41	0.05	0.07	0.02
1.00	7,585	5,358	0.41	605,610	0	107,956	0	nan	0.00	0.00	0.00

BRFC\_5\_Fold\_alpha\_balanced\_Easy\_Test



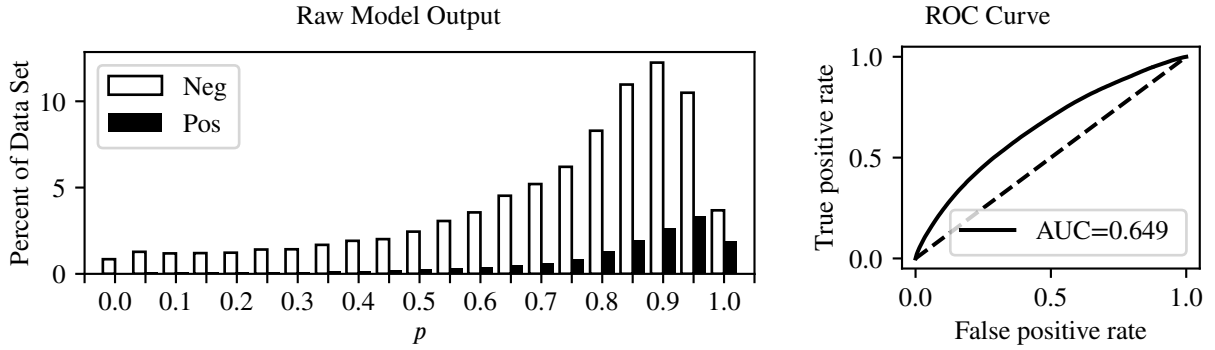
	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
p											
0.00	3,512	133	0.04	3,512	602,098	133	107,823	0.15	1.00	5.58	0.99
0.05	9,244	522	0.05	12,756	592,854	655	107,301	0.15	0.99	5.49	0.98
0.10	8,796	589	0.06	21,552	584,058	1,244	106,712	0.15	0.99	5.41	0.97
0.15	8,659	591	0.06	30,211	575,399	1,835	106,121	0.16	0.98	5.33	0.96
0.20	9,124	751	0.08	39,335	566,275	2,586	105,370	0.16	0.98	5.25	0.94
0.25	9,996	824	0.08	49,331	556,279	3,410	104,546	0.16	0.97	5.15	0.93
0.30	10,552	813	0.07	59,883	545,727	4,223	103,733	0.16	0.96	5.06	0.91
0.35	12,141	1,035	0.08	72,024	533,586	5,258	102,698	0.16	0.95	4.94	0.89
0.40	13,923	1,256	0.08	85,947	519,663	6,514	101,442	0.16	0.94	4.81	0.87
0.45	14,760	1,448	0.09	100,707	504,903	7,962	99,994	0.17	0.93	4.68	0.85
0.50	17,966	1,843	0.09	118,673	486,937	9,805	98,151	0.17	0.91	4.51	0.82
0.55	22,537	2,254	0.09	141,210	464,400	12,059	95,897	0.17	0.89	4.30	0.79
0.60	26,529	2,760	0.09	167,739	437,871	14,819	93,137	0.18	0.86	4.06	0.74
0.65	33,757	3,642	0.10	201,496	404,114	18,461	89,495	0.18	0.83	3.74	0.69
0.70	38,864	4,753	0.11	240,360	365,250	23,214	84,742	0.19	0.78	3.38	0.63
0.75	47,333	6,655	0.12	287,693	317,917	29,869	78,087	0.20	0.72	2.94	0.55
0.80	63,853	10,001	0.14	351,546	254,064	39,870	68,086	0.21	0.63	2.35	0.45
0.85	86,113	15,482	0.15	437,659	167,951	55,352	52,604	0.24	0.49	1.56	0.31
0.90	87,968	20,897	0.19	525,627	79,983	76,249	31,707	0.28	0.29	0.74	0.16
0.95	66,409	23,607	0.26	592,036	13,574	99,856	8,100	0.37	0.08	0.13	0.03
1.00	13,574	8,100	0.37	605,610	0	107,956	0	nan	0.00	0.00	0.00

BRFC\_5\_Fold\_alpha\_balanced\_Easy\_Test\_Transformed\_100



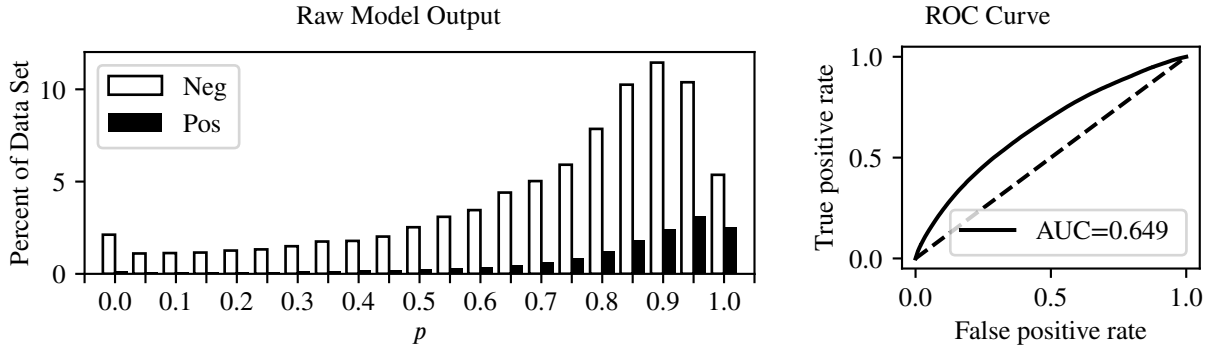
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	3,512	133	0.04	3,512	602,098	133	107,823	0.15	1.00	5.58	0.99
0.05	9,244	522	0.05	12,756	592,854	655	107,301	0.15	0.99	5.49	0.98
0.10	8,796	589	0.06	21,552	584,058	1,244	106,712	0.15	0.99	5.41	0.97
0.15	8,659	591	0.06	30,211	575,399	1,835	106,121	0.16	0.98	5.33	0.96
0.20	9,124	751	0.08	39,335	566,275	2,586	105,370	0.16	0.98	5.25	0.94
0.25	9,996	824	0.08	49,331	556,279	3,410	104,546	0.16	0.97	5.15	0.93
0.30	10,552	813	0.07	59,883	545,727	4,223	103,733	0.16	0.96	5.06	0.91
0.35	12,141	1,035	0.08	72,024	533,586	5,258	102,698	0.16	0.95	4.94	0.89
0.40	13,923	1,256	0.08	85,947	519,663	6,514	101,442	0.16	0.94	4.81	0.87
0.45	14,760	1,448	0.09	100,707	504,903	7,962	99,994	0.17	0.93	4.68	0.85
0.50	17,966	1,843	0.09	118,673	486,937	9,805	98,151	0.17	0.91	4.51	0.82
0.55	22,537	2,254	0.09	141,210	464,400	12,059	95,897	0.17	0.89	4.30	0.79
0.60	26,529	2,760	0.09	167,739	437,871	14,819	93,137	0.18	0.86	4.06	0.74
0.65	33,757	3,642	0.10	201,496	404,114	18,461	89,495	0.18	0.83	3.74	0.69
0.70	38,864	4,753	0.11	240,360	365,250	23,214	84,742	0.19	0.78	3.38	0.63
0.75	47,333	6,655	0.12	287,693	317,917	29,869	78,087	0.20	0.72	2.94	0.55
0.80	63,853	10,001	0.14	351,546	254,064	39,870	68,086	0.21	0.63	2.35	0.45
0.85	86,113	15,482	0.15	437,659	167,951	55,352	52,604	0.24	0.49	1.56	0.31
0.90	87,968	20,897	0.19	525,627	79,983	76,249	31,707	0.28	0.29	0.74	0.16
0.95	66,409	23,607	0.26	592,036	13,574	99,856	8,100	0.37	0.08	0.13	0.03
1.00	13,574	8,100	0.37	605,610	0	107,956	0	nan	0.00	0.00	0.00

BRFC\_5\_Fold\_alpha\_balanced\_Easy\_Test\_Transformed\_98



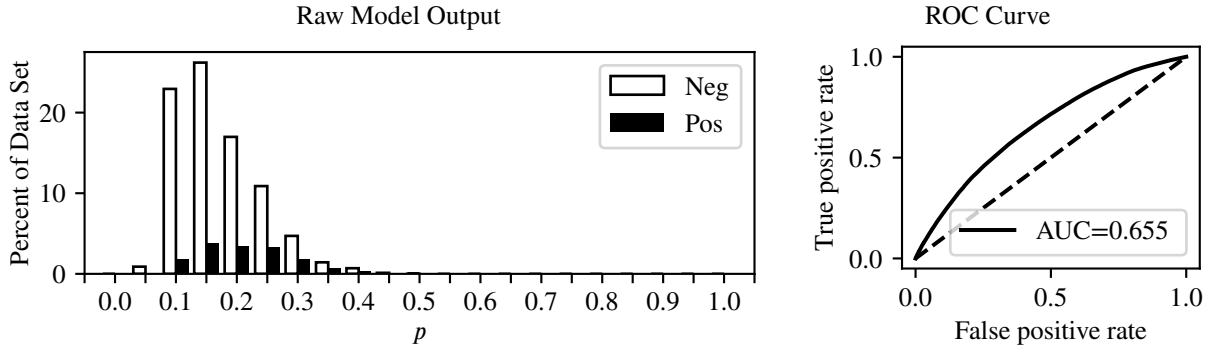
	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
$p$											
0.00	6,060	265	0.04	6,060	599,550	265	107,691	0.15	1.00	5.55	0.99
0.05	9,112	568	0.06	15,172	590,438	833	107,123	0.15	0.99	5.47	0.98
0.10	8,460	567	0.06	23,632	581,978	1,400	106,556	0.15	0.99	5.39	0.96
0.15	8,578	593	0.06	32,210	573,400	1,993	105,963	0.16	0.98	5.31	0.95
0.20	8,750	734	0.08	40,960	564,650	2,727	105,229	0.16	0.97	5.23	0.94
0.25	10,066	799	0.07	51,026	554,584	3,526	104,430	0.16	0.97	5.14	0.92
0.30	10,162	810	0.07	61,188	544,422	4,336	103,620	0.16	0.96	5.04	0.91
0.35	11,988	1,027	0.08	73,176	532,434	5,363	102,593	0.16	0.95	4.93	0.89
0.40	13,656	1,230	0.08	86,832	518,778	6,593	101,363	0.16	0.94	4.81	0.87
0.45	14,359	1,405	0.09	101,191	504,419	7,998	99,958	0.17	0.93	4.67	0.85
0.50	17,461	1,805	0.09	118,652	486,958	9,803	98,153	0.17	0.91	4.51	0.82
0.55	21,860	2,179	0.09	140,512	465,098	11,982	95,974	0.17	0.89	4.31	0.79
0.60	25,410	2,652	0.09	165,922	439,688	14,634	93,322	0.18	0.86	4.07	0.75
0.65	32,305	3,446	0.10	198,227	407,383	18,080	89,876	0.18	0.83	3.77	0.70
0.70	37,133	4,500	0.11	235,360	370,250	22,580	85,376	0.19	0.79	3.43	0.64
0.75	44,258	6,053	0.12	279,618	325,992	28,633	79,323	0.20	0.73	3.02	0.57
0.80	59,188	9,168	0.13	338,806	266,804	37,801	70,155	0.21	0.65	2.47	0.47
0.85	78,278	13,694	0.15	417,084	188,526	51,495	56,461	0.23	0.52	1.75	0.34
0.90	87,355	18,948	0.18	504,439	101,171	70,443	37,513	0.27	0.35	0.94	0.19
0.95	74,899	23,875	0.24	579,338	26,272	94,318	13,638	0.34	0.13	0.24	0.06
1.00	26,272	13,638	0.34	605,610	0	107,956	0	nan	0.00	0.00	0.00

BRFC\_5\_Fold\_alpha\_balanced\_Easy\_Test\_Transformed\_95



$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	15,142	830	0.05	15,142	590,468	830	107,126	0.15	0.99	5.47	0.98
0.05	7,881	534	0.06	23,023	582,587	1,364	106,592	0.15	0.99	5.40	0.97
0.10	8,038	546	0.06	31,061	574,549	1,910	106,046	0.16	0.98	5.32	0.95
0.15	8,240	673	0.08	39,301	566,309	2,583	105,373	0.16	0.98	5.25	0.94
0.20	9,008	744	0.08	48,309	557,301	3,327	104,629	0.16	0.97	5.16	0.93
0.25	9,459	714	0.07	57,768	547,842	4,041	103,915	0.16	0.96	5.07	0.91
0.30	10,682	905	0.08	68,450	537,160	4,946	103,010	0.16	0.95	4.98	0.90
0.35	12,502	1,093	0.08	80,952	524,658	6,039	101,917	0.16	0.94	4.86	0.88
0.40	12,741	1,223	0.09	93,693	511,917	7,262	100,694	0.16	0.93	4.74	0.86
0.45	14,417	1,477	0.09	108,110	497,500	8,739	99,217	0.17	0.92	4.61	0.84
0.50	18,024	1,852	0.09	126,134	479,476	10,591	97,365	0.17	0.90	4.44	0.81
0.55	22,055	2,155	0.09	148,189	457,421	12,746	95,210	0.17	0.88	4.24	0.77
0.60	24,648	2,603	0.10	172,837	432,773	15,349	92,607	0.18	0.86	4.01	0.74
0.65	31,434	3,442	0.10	204,271	401,339	18,791	89,165	0.18	0.83	3.72	0.69
0.70	35,871	4,387	0.11	240,142	365,468	23,178	84,778	0.19	0.79	3.39	0.63
0.75	42,197	5,911	0.12	282,339	323,271	29,089	78,867	0.20	0.73	2.99	0.56
0.80	56,051	8,632	0.13	338,390	267,220	37,721	70,235	0.21	0.65	2.48	0.47
0.85	73,150	12,767	0.15	411,540	194,070	50,488	57,468	0.23	0.53	1.80	0.35
0.90	81,687	17,103	0.17	493,227	112,383	67,591	40,365	0.26	0.37	1.04	0.21
0.95	74,088	22,217	0.23	567,315	38,295	89,808	18,148	0.32	0.17	0.35	0.08
1.00	38,295	18,148	0.32	605,610	0	107,956	0	nan	0.00	0.00	0.00

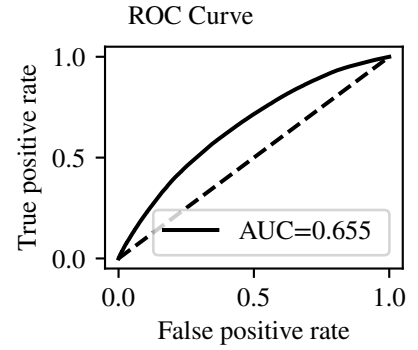
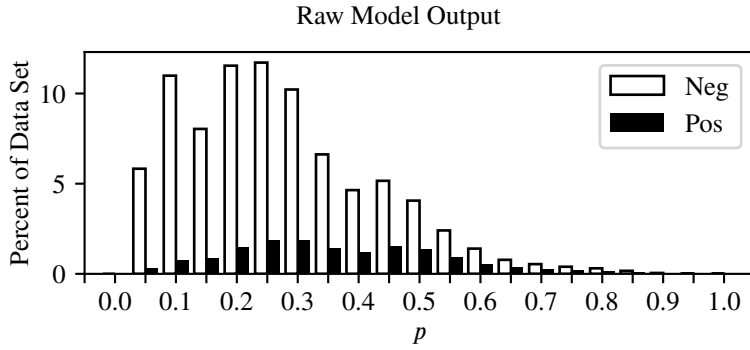
LogReg\_5\_Fold\_alpha\_0\_5\_Easy\_Test



	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
p											
0.00	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.05	6,366	280	0.04	6,366	599,244	280	107,676	0.15	1.00	5.55	0.99
0.10	163,677	12,467	0.07	170,043	435,567	12,747	95,209	0.18	0.88	4.03	0.74
0.15	186,963	26,933	0.13	357,006	248,604	39,680	68,276	0.22	0.63	2.30	0.44
0.20	121,216	24,671	0.17	478,222	127,388	64,351	43,605	0.26	0.40	1.18	0.24
0.25	77,675	23,446	0.23	555,897	49,713	87,797	20,159	0.29	0.19	0.46	0.10
0.30	33,590	12,576	0.27	589,487	16,123	100,373	7,583	0.32	0.07	0.15	0.03
0.35	10,212	4,585	0.31	599,699	5,911	104,958	2,998	0.34	0.03	0.05	0.01
0.40	4,989	2,443	0.33	604,688	922	107,401	555	0.38	0.01	0.01	0.00
0.45	916	548	0.37	605,604	6	107,949	7	0.54	0.00	0.00	0.00
0.50	6	7	0.54	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.55	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.60	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.65	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.70	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.75	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.80	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.85	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.90	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.95	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
1.00	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00

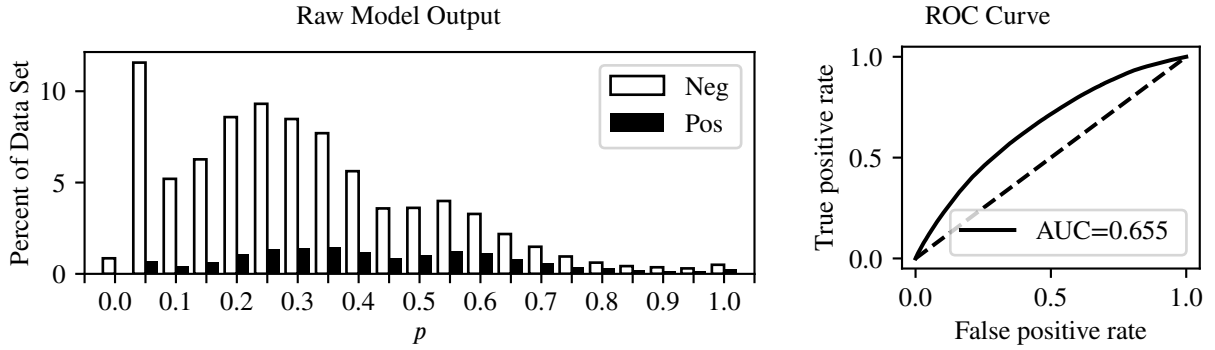


LogReg\_5\_Fold\_alpha\_0\_5\_Easy\_Test\_Transformed\_100



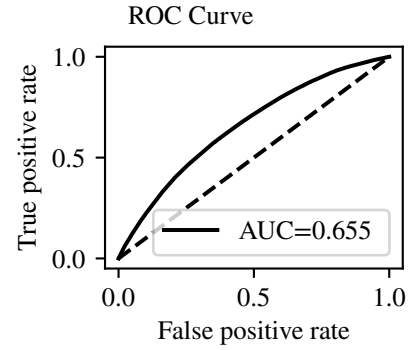
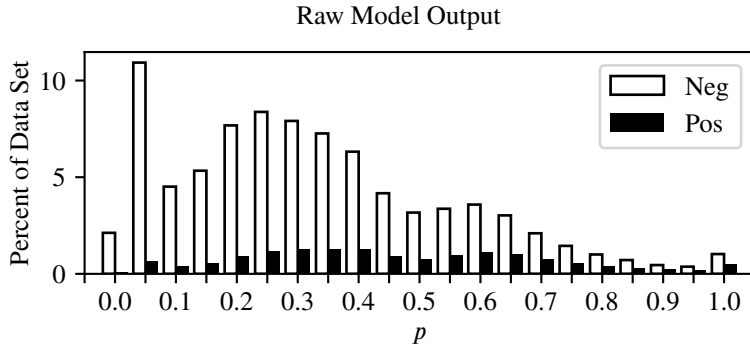
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	1	0	0.00	1	605,609	0	107,956	0.15	1.00	5.61	1.00
0.05	41,598	2,184	0.05	41,599	564,011	2,184	105,772	0.16	0.98	5.22	0.94
0.10	78,415	5,423	0.06	120,014	485,596	7,607	100,349	0.17	0.93	4.50	0.82
0.15	57,340	5,945	0.09	177,354	428,256	13,552	94,404	0.18	0.87	3.97	0.73
0.20	82,367	10,669	0.11	259,721	345,889	24,221	83,735	0.19	0.78	3.20	0.60
0.25	83,586	13,068	0.14	343,307	262,303	37,289	70,667	0.21	0.65	2.43	0.47
0.30	72,942	13,452	0.16	416,249	189,361	50,741	57,215	0.23	0.53	1.75	0.35
0.35	47,266	10,196	0.18	463,515	142,095	60,937	47,019	0.25	0.44	1.32	0.27
0.40	33,131	8,361	0.20	496,646	108,964	69,298	38,658	0.26	0.36	1.01	0.21
0.45	36,811	10,969	0.23	533,457	72,153	80,267	27,689	0.28	0.26	0.67	0.14
0.50	28,970	9,859	0.25	562,427	43,183	90,126	17,830	0.29	0.17	0.40	0.09
0.55	17,177	6,456	0.27	579,604	26,006	96,582	11,374	0.30	0.11	0.24	0.05
0.60	9,987	3,836	0.28	589,591	16,019	100,418	7,538	0.32	0.07	0.15	0.03
0.65	5,547	2,459	0.31	595,138	10,472	102,877	5,079	0.33	0.05	0.10	0.02
0.70	3,848	1,748	0.31	598,986	6,624	104,625	3,331	0.33	0.03	0.06	0.01
0.75	2,816	1,283	0.31	601,802	3,808	105,908	2,048	0.35	0.02	0.04	0.01
0.80	2,189	1,117	0.34	603,991	1,619	107,025	931	0.37	0.01	0.01	0.00
0.85	1,200	662	0.36	605,191	419	107,687	269	0.39	0.00	0.00	0.00
0.90	348	232	0.40	605,539	71	107,919	37	0.34	0.00	0.00	0.00
0.95	66	31	0.32	605,605	5	107,950	6	0.55	0.00	0.00	0.00
1.00	5	6	0.55	605,610	0	107,956	0	nan	0.00	0.00	0.00

LogReg\_5\_Fold\_alpha\_0.5\_Easy\_Test\_Transformed\_98



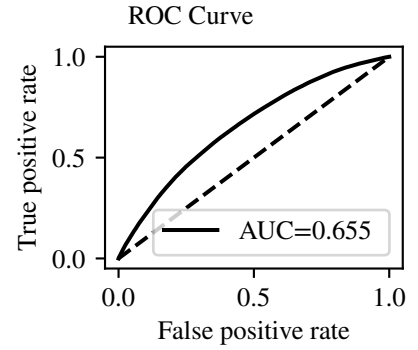
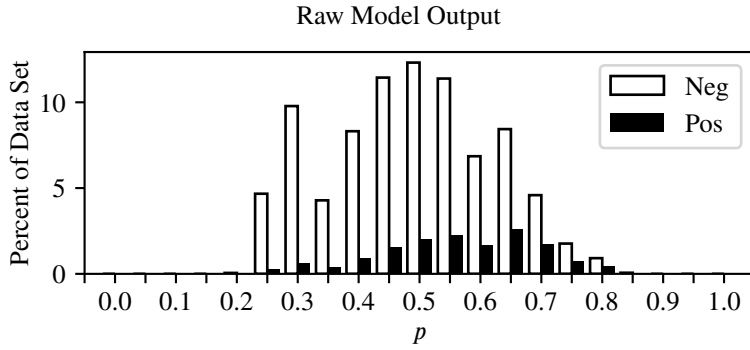
	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
p											
0.00	6,081	270	0.04	6,081	599,529	270	107,686	0.15	1.00	5.55	0.99
0.05	82,547	4,886	0.06	88,628	516,982	5,156	102,800	0.17	0.95	4.79	0.87
0.10	37,122	2,969	0.07	125,750	479,860	8,125	99,831	0.17	0.92	4.44	0.81
0.15	44,736	4,680	0.09	170,486	435,124	12,805	95,151	0.18	0.88	4.03	0.74
0.20	61,251	7,460	0.11	231,737	373,873	20,265	87,691	0.19	0.81	3.46	0.65
0.25	66,442	9,712	0.13	298,179	307,431	29,977	77,979	0.20	0.72	2.85	0.54
0.30	60,500	9,992	0.14	358,679	246,931	39,969	67,987	0.22	0.63	2.29	0.44
0.35	54,966	10,227	0.16	413,645	191,965	50,196	57,760	0.23	0.54	1.78	0.35
0.40	40,119	8,472	0.17	453,764	151,846	58,668	49,288	0.25	0.46	1.41	0.28
0.45	25,570	5,920	0.19	479,334	126,276	64,588	43,368	0.26	0.40	1.17	0.24
0.50	25,787	7,095	0.22	505,121	100,489	71,683	36,273	0.27	0.34	0.93	0.19
0.55	28,474	8,627	0.23	533,595	72,015	80,310	27,646	0.28	0.26	0.67	0.14
0.60	23,409	7,827	0.25	557,004	48,606	88,137	19,819	0.29	0.18	0.45	0.10
0.65	15,563	5,733	0.27	572,567	33,043	93,870	14,086	0.30	0.13	0.31	0.07
0.70	10,588	4,090	0.28	583,155	22,455	97,960	9,996	0.31	0.09	0.21	0.05
0.75	6,785	2,598	0.28	589,940	15,670	100,558	7,398	0.32	0.07	0.15	0.03
0.80	4,390	1,966	0.31	594,330	11,280	102,524	5,432	0.33	0.05	0.10	0.02
0.85	3,027	1,362	0.31	597,357	8,253	103,886	4,070	0.33	0.04	0.08	0.02
0.90	2,572	1,169	0.31	599,929	5,681	105,055	2,901	0.34	0.03	0.05	0.01
0.95	2,132	978	0.31	602,061	3,549	106,033	1,923	0.35	0.02	0.03	0.01
1.00	3,549	1,923	0.35	605,610	0	107,956	0	nan	0.00	0.00	0.00

LogReg\_5\_Fold\_alpha\_0\_5\_Easy\_Test\_Transformed\_95



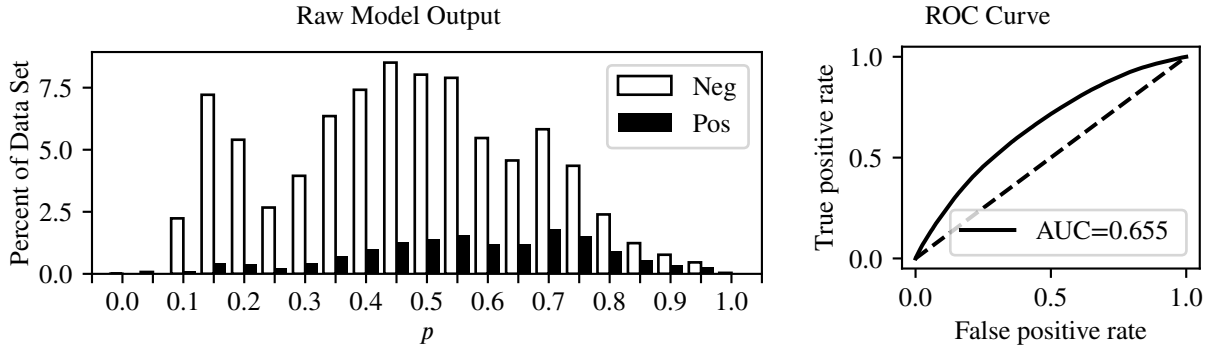
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	15,144	729	0.05	15,144	590,466	729	107,227	0.15	0.99	5.47	0.98
0.05	77,976	4,752	0.06	93,120	512,490	5,481	102,475	0.17	0.95	4.75	0.86
0.10	32,193	2,609	0.07	125,313	480,297	8,090	99,866	0.17	0.93	4.45	0.81
0.15	38,067	4,002	0.10	163,380	442,230	12,092	95,864	0.18	0.89	4.10	0.75
0.20	54,790	6,442	0.11	218,170	387,440	18,534	89,422	0.19	0.83	3.59	0.67
0.25	59,772	8,354	0.12	277,942	327,668	26,888	81,068	0.20	0.75	3.04	0.57
0.30	56,440	8,897	0.14	334,382	271,228	35,785	72,171	0.21	0.67	2.51	0.48
0.35	51,824	9,059	0.15	386,206	219,404	44,844	63,112	0.22	0.58	2.03	0.40
0.40	45,092	9,101	0.17	431,298	174,312	53,945	54,011	0.24	0.50	1.61	0.32
0.45	29,756	6,390	0.18	461,054	144,556	60,335	47,621	0.25	0.44	1.34	0.27
0.50	22,622	5,367	0.19	483,676	121,934	65,702	42,254	0.26	0.39	1.13	0.23
0.55	24,030	6,665	0.22	507,706	97,904	72,367	35,589	0.27	0.33	0.91	0.19
0.60	25,573	7,821	0.23	533,279	72,331	80,188	27,768	0.28	0.26	0.67	0.14
0.65	21,581	7,230	0.25	554,860	50,750	87,418	20,538	0.29	0.19	0.47	0.10
0.70	14,978	5,422	0.27	569,838	35,772	92,840	15,116	0.30	0.14	0.33	0.07
0.75	10,328	3,963	0.28	580,166	25,444	96,803	11,153	0.30	0.10	0.24	0.05
0.80	7,149	2,733	0.28	587,315	18,295	99,536	8,420	0.32	0.08	0.17	0.04
0.85	5,094	2,118	0.29	592,409	13,201	101,654	6,302	0.32	0.06	0.12	0.03
0.90	3,245	1,481	0.31	595,654	9,956	103,135	4,821	0.33	0.04	0.09	0.02
0.95	2,646	1,182	0.31	598,300	7,310	104,317	3,639	0.33	0.03	0.07	0.02
1.00	7,310	3,639	0.33	605,610	0	107,956	0	nan	0.00	0.00	0.00

LogReg\_5\_Fold\_alpha\_balanced\_Easy\_Test



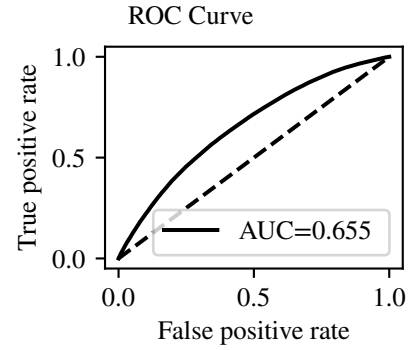
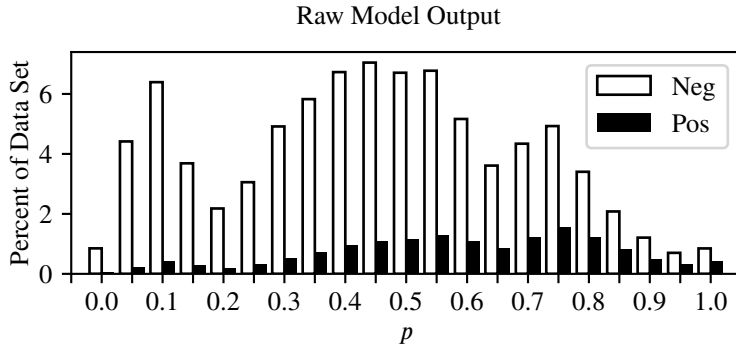
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.05	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.10	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.15	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.20	389	13	0.03	389	605,221	13	107,943	0.15	1.00	5.61	1.00
0.25	33,328	1,683	0.05	33,717	571,893	1,696	106,260	0.16	0.98	5.30	0.95
0.30	69,794	4,545	0.06	103,511	502,099	6,241	101,715	0.17	0.94	4.65	0.85
0.35	30,575	2,674	0.08	134,086	471,524	8,915	99,041	0.17	0.92	4.37	0.80
0.40	59,327	6,558	0.10	193,413	412,197	15,473	92,483	0.18	0.86	3.82	0.71
0.45	81,635	10,972	0.12	275,048	330,562	26,445	81,511	0.20	0.76	3.06	0.58
0.50	87,874	14,229	0.14	362,922	242,688	40,674	67,282	0.22	0.62	2.25	0.43
0.55	81,239	15,960	0.16	444,161	161,449	56,634	51,322	0.24	0.48	1.50	0.30
0.60	48,923	11,693	0.19	493,084	112,526	68,327	39,629	0.26	0.37	1.04	0.21
0.65	60,209	18,613	0.24	553,293	52,317	86,940	21,016	0.29	0.19	0.48	0.10
0.70	32,734	12,183	0.27	586,027	19,583	99,123	8,833	0.31	0.08	0.18	0.04
0.75	12,595	5,357	0.30	598,622	6,988	104,480	3,476	0.33	0.03	0.06	0.01
0.80	6,528	3,183	0.33	605,150	460	107,663	293	0.39	0.00	0.00	0.00
0.85	460	293	0.39	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.90	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.95	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
1.00	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00

LogReg\_5\_Fold\_alpha\_balanced\_Easy\_Test\_Transformed\_100



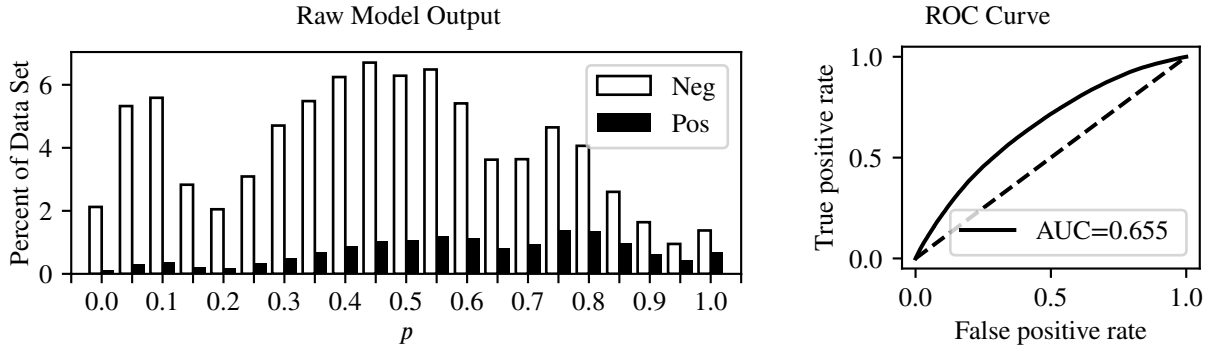
	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
p											
0.00	1	0	0.00	1	605,609	0	107,956	0.15	1.00	5.61	1.00
0.05	541	21	0.04	542	605,068	21	107,935	0.15	1.00	5.60	1.00
0.10	15,950	749	0.04	16,492	589,118	770	107,186	0.15	0.99	5.46	0.98
0.15	51,474	2,948	0.05	67,966	537,644	3,718	104,238	0.16	0.97	4.98	0.90
0.20	38,555	2,758	0.07	106,521	499,089	6,476	101,480	0.17	0.94	4.62	0.84
0.25	19,063	1,634	0.08	125,584	480,026	8,110	99,846	0.17	0.92	4.45	0.81
0.30	28,182	2,896	0.09	153,766	451,844	11,006	96,950	0.18	0.90	4.19	0.77
0.35	45,347	5,113	0.10	199,113	406,497	16,119	91,837	0.18	0.85	3.77	0.70
0.40	52,910	6,931	0.12	252,023	353,587	23,050	84,906	0.19	0.79	3.28	0.61
0.45	60,726	9,106	0.13	312,749	292,861	32,156	75,800	0.21	0.70	2.71	0.52
0.50	57,265	9,774	0.15	370,014	235,596	41,930	66,026	0.22	0.61	2.18	0.42
0.55	56,345	10,938	0.16	426,359	179,251	52,868	55,088	0.24	0.51	1.66	0.33
0.60	39,044	8,516	0.18	465,403	140,207	61,384	46,572	0.25	0.43	1.30	0.26
0.65	32,592	8,357	0.20	497,995	107,615	69,741	38,215	0.26	0.35	1.00	0.20
0.70	41,566	12,686	0.23	539,561	66,049	82,427	25,529	0.28	0.24	0.61	0.13
0.75	31,063	10,752	0.26	570,624	34,986	93,179	14,777	0.30	0.14	0.32	0.07
0.80	17,082	6,549	0.28	587,706	17,904	99,728	8,228	0.31	0.08	0.17	0.04
0.85	8,830	3,797	0.30	596,536	9,074	103,525	4,431	0.33	0.04	0.08	0.02
0.90	5,494	2,535	0.32	602,030	3,580	106,060	1,896	0.35	0.02	0.03	0.01
0.95	3,300	1,735	0.34	605,330	280	107,795	161	0.37	0.00	0.00	0.00
1.00	280	161	0.37	605,610	0	107,956	0	nan	0.00	0.00	0.00

LogReg\_5\_Fold\_alpha\_balanced\_Easy\_Test\_Transformed\_98



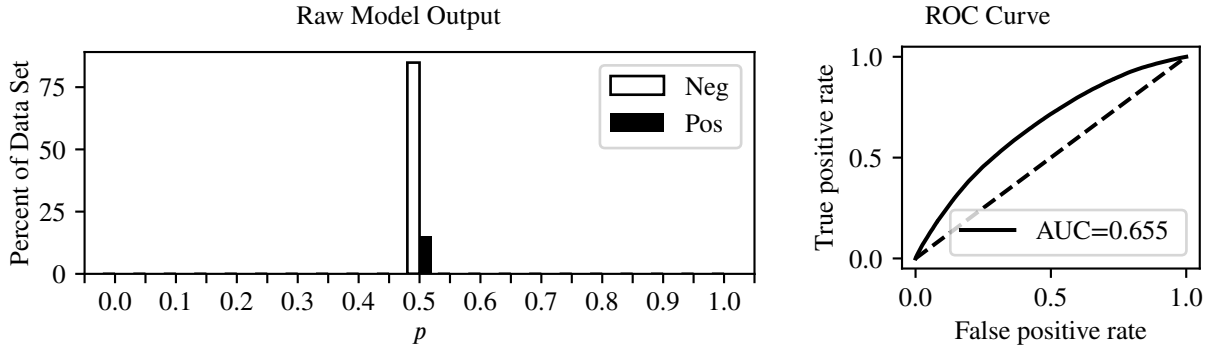
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	6,069	251	0.04	6,069	599,541	251	107,705	0.15	1.00	5.55	0.99
0.05	31,514	1,662	0.05	37,583	568,027	1,913	106,043	0.16	0.98	5.26	0.94
0.10	45,619	2,872	0.06	83,202	522,408	4,785	103,171	0.16	0.96	4.84	0.88
0.15	26,307	1,925	0.07	109,509	496,101	6,710	101,246	0.17	0.94	4.60	0.84
0.20	15,558	1,336	0.08	125,067	480,543	8,046	99,910	0.17	0.93	4.45	0.81
0.25	21,811	2,257	0.09	146,878	458,732	10,303	97,653	0.18	0.90	4.25	0.78
0.30	35,079	3,744	0.10	181,957	423,653	14,047	93,909	0.18	0.87	3.92	0.73
0.35	41,581	5,118	0.11	223,538	382,072	19,165	88,791	0.19	0.82	3.54	0.66
0.40	48,014	6,772	0.12	271,552	334,058	25,937	82,019	0.20	0.76	3.09	0.58
0.45	50,275	7,746	0.13	321,827	283,783	33,683	74,273	0.21	0.69	2.63	0.50
0.50	47,863	8,195	0.15	369,690	235,920	41,878	66,078	0.22	0.61	2.19	0.42
0.55	48,341	9,235	0.16	418,031	187,579	51,113	56,843	0.23	0.53	1.74	0.34
0.60	36,857	7,727	0.17	454,888	150,722	58,840	49,116	0.25	0.45	1.40	0.28
0.65	25,764	6,186	0.19	480,652	124,958	65,026	42,930	0.26	0.40	1.16	0.24
0.70	30,975	8,575	0.22	511,627	93,983	73,601	34,355	0.27	0.32	0.87	0.18
0.75	35,171	11,160	0.24	546,798	58,812	84,761	23,195	0.28	0.21	0.54	0.11
0.80	24,289	8,574	0.26	571,087	34,523	93,335	14,621	0.30	0.14	0.32	0.07
0.85	14,849	5,751	0.28	585,936	19,674	99,086	8,870	0.31	0.08	0.18	0.04
0.90	8,620	3,554	0.29	594,556	11,054	102,640	5,316	0.32	0.05	0.10	0.02
0.95	5,001	2,260	0.31	599,557	6,053	104,900	3,056	0.34	0.03	0.06	0.01
1.00	6,053	3,056	0.34	605,610	0	107,956	0	nan	0.00	0.00	0.00

LogReg\_5\_Fold\_alpha\_balanced\_Easy\_Test\_Transformed\_95



p	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	15,153	692	0.04	15,153	590,457	692	107,264	0.15	0.99	5.47	0.98
0.05	37,994	2,108	0.05	53,147	552,463	2,800	105,156	0.16	0.97	5.12	0.92
0.10	39,872	2,662	0.06	93,019	512,591	5,462	102,494	0.17	0.95	4.75	0.86
0.15	20,187	1,503	0.07	113,206	492,404	6,965	100,991	0.17	0.94	4.56	0.83
0.20	14,624	1,338	0.08	127,830	477,780	8,303	99,653	0.17	0.92	4.43	0.81
0.25	22,051	2,297	0.09	149,881	455,729	10,600	97,356	0.18	0.90	4.22	0.78
0.30	33,583	3,611	0.10	183,464	422,146	14,211	93,745	0.18	0.87	3.91	0.72
0.35	39,123	4,839	0.11	222,587	383,023	19,050	88,906	0.19	0.82	3.55	0.66
0.40	44,571	6,219	0.12	267,158	338,452	25,269	82,687	0.20	0.77	3.14	0.59
0.45	47,841	7,258	0.13	314,999	290,611	32,527	75,429	0.21	0.70	2.69	0.51
0.50	44,869	7,576	0.14	359,868	245,742	40,103	67,853	0.22	0.63	2.28	0.44
0.55	46,280	8,579	0.16	406,148	199,462	48,682	59,274	0.23	0.55	1.85	0.36
0.60	38,604	8,063	0.17	444,752	160,858	56,745	51,211	0.24	0.47	1.49	0.30
0.65	25,860	5,855	0.18	470,612	134,998	62,600	45,356	0.25	0.42	1.25	0.25
0.70	25,967	6,733	0.21	496,579	109,031	69,333	38,623	0.26	0.36	1.01	0.21
0.75	33,171	9,810	0.23	529,750	75,860	79,143	28,813	0.28	0.27	0.70	0.15
0.80	28,992	9,645	0.25	558,742	46,868	88,788	19,168	0.29	0.18	0.43	0.09
0.85	18,570	6,948	0.27	577,312	28,298	95,736	12,220	0.30	0.11	0.26	0.06
0.90	11,696	4,490	0.28	589,008	16,602	100,226	7,730	0.32	0.07	0.15	0.03
0.95	6,776	2,962	0.30	595,784	9,826	103,188	4,768	0.33	0.04	0.09	0.02
1.00	9,826	4,768	0.33	605,610	0	107,956	0	nan	0.00	0.00	0.00

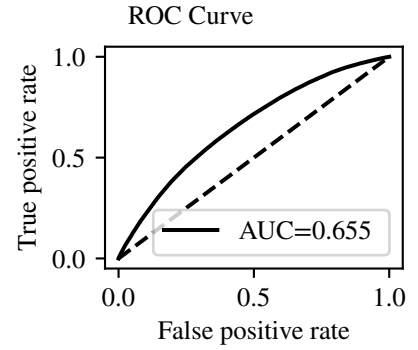
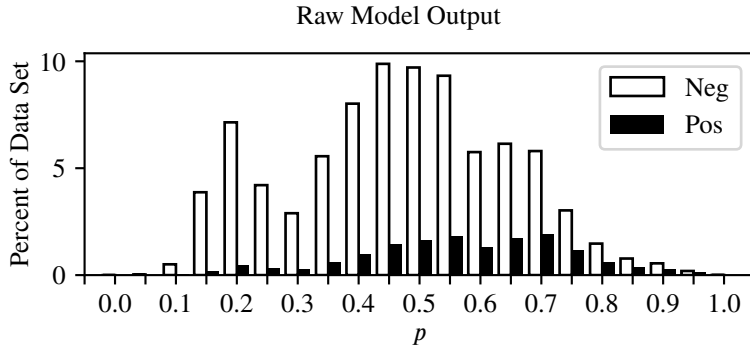
AdaBoost\_5\_Fold\_Easy\_Test



	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
p											
0.00	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.05	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.10	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.15	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.20	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.25	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.30	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.35	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.40	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.45	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.50	605,610	107,956	0.15	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.55	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.60	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.65	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.70	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.75	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.80	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.85	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.90	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.95	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
1.00	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00

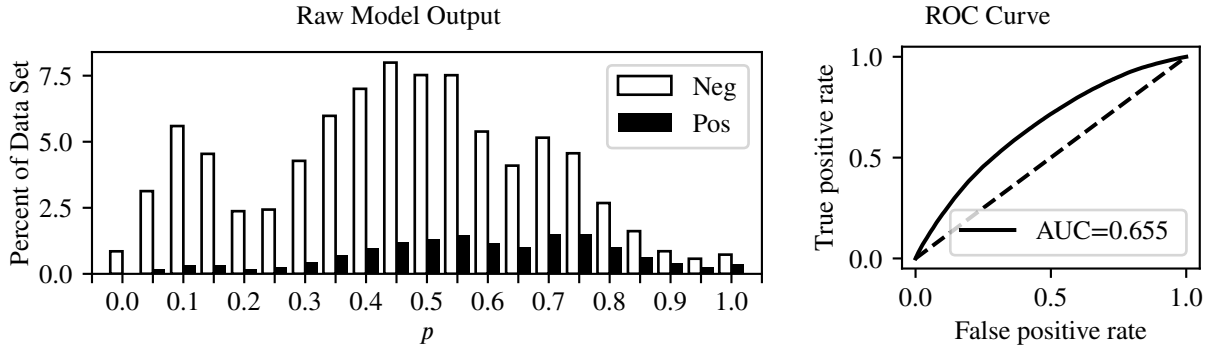


AdaBoost\_5\_Fold\_Easy\_Test\_Transformed\_100



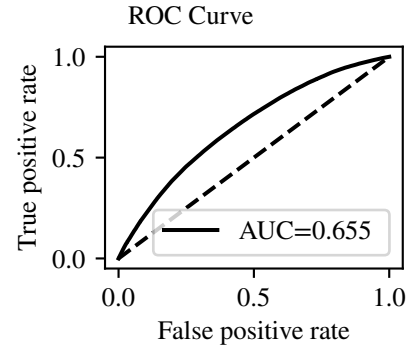
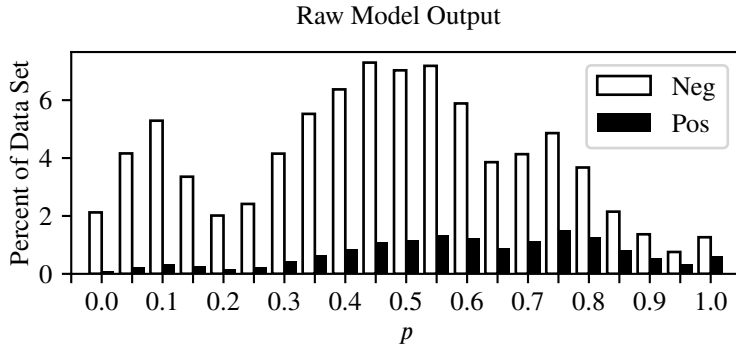
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	1	0	0.00	1	605,609	0	107,956	0.15	1.00	5.61	1.00
0.05	195	4	0.02	196	605,414	4	107,952	0.15	1.00	5.61	1.00
0.10	3,601	158	0.04	3,797	601,813	162	107,794	0.15	1.00	5.57	0.99
0.15	27,650	1,404	0.05	31,447	574,163	1,566	106,390	0.16	0.99	5.32	0.95
0.20	50,981	3,166	0.06	82,428	523,182	4,732	103,224	0.16	0.96	4.85	0.88
0.25	30,024	2,178	0.07	112,452	493,158	6,910	101,046	0.17	0.94	4.57	0.83
0.30	20,651	1,915	0.08	133,103	472,507	8,825	99,131	0.17	0.92	4.38	0.80
0.35	39,673	4,216	0.10	172,776	432,834	13,041	94,915	0.18	0.88	4.01	0.74
0.40	57,218	7,012	0.11	229,994	375,616	20,053	87,903	0.19	0.81	3.48	0.65
0.45	70,503	10,201	0.13	300,497	305,113	30,254	77,702	0.20	0.72	2.83	0.54
0.50	69,285	11,656	0.14	369,782	235,828	41,910	66,046	0.22	0.61	2.18	0.42
0.55	66,537	13,028	0.16	436,319	169,291	54,938	53,018	0.24	0.49	1.57	0.31
0.60	41,052	9,246	0.18	477,371	128,239	64,184	43,772	0.25	0.41	1.19	0.24
0.65	43,838	12,329	0.22	521,209	84,401	76,513	31,443	0.27	0.29	0.78	0.16
0.70	41,399	13,731	0.25	562,608	43,002	90,244	17,712	0.29	0.16	0.40	0.09
0.75	21,598	8,140	0.27	584,206	21,404	98,384	9,572	0.31	0.09	0.20	0.04
0.80	10,515	4,338	0.29	594,721	10,889	102,722	5,234	0.32	0.05	0.10	0.02
0.85	5,532	2,522	0.31	600,253	5,357	105,244	2,712	0.34	0.03	0.05	0.01
0.90	3,929	1,889	0.32	604,182	1,428	107,133	823	0.37	0.01	0.01	0.00
0.95	1,376	791	0.37	605,558	52	107,924	32	0.38	0.00	0.00	0.00
1.00	52	32	0.38	605,610	0	107,956	0	nan	0.00	0.00	0.00

AdaBoost\_5\_Fold\_Easy\_Test\_Transformed\_98



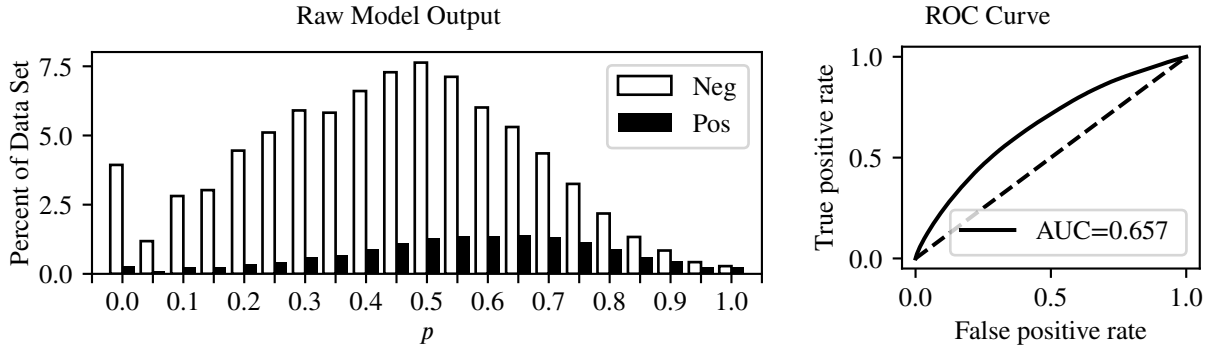
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	6,087	256	0.04	6,087	599,523	256	107,700	0.15	1.00	5.55	0.99
0.05	22,341	1,164	0.05	28,428	577,182	1,420	106,536	0.16	0.99	5.35	0.96
0.10	39,916	2,319	0.05	68,344	537,266	3,739	104,217	0.16	0.97	4.98	0.90
0.15	32,408	2,279	0.07	100,752	504,858	6,018	101,938	0.17	0.94	4.68	0.85
0.20	16,925	1,327	0.07	117,677	487,933	7,345	100,611	0.17	0.93	4.52	0.82
0.25	17,358	1,670	0.09	135,035	470,575	9,015	98,941	0.17	0.92	4.36	0.80
0.30	30,514	3,234	0.10	165,549	440,061	12,249	95,707	0.18	0.89	4.08	0.75
0.35	42,668	4,941	0.10	208,217	397,393	17,190	90,766	0.19	0.84	3.68	0.68
0.40	49,966	6,845	0.12	258,183	347,427	24,035	83,921	0.19	0.78	3.22	0.60
0.45	57,050	8,536	0.13	315,233	290,377	32,571	75,385	0.21	0.70	2.69	0.51
0.50	53,686	9,186	0.15	368,919	236,691	41,757	66,199	0.22	0.61	2.19	0.42
0.55	53,648	10,358	0.16	422,567	183,043	52,115	55,841	0.23	0.52	1.70	0.33
0.60	38,431	8,247	0.18	460,998	144,612	60,362	47,594	0.25	0.44	1.34	0.27
0.65	29,228	7,158	0.20	490,226	115,384	67,520	40,436	0.26	0.37	1.07	0.22
0.70	36,772	10,776	0.23	526,998	78,612	78,296	29,660	0.27	0.27	0.73	0.15
0.75	32,564	10,772	0.25	559,562	46,048	89,068	18,888	0.29	0.17	0.43	0.09
0.80	19,129	7,222	0.27	578,691	26,919	96,290	11,666	0.30	0.11	0.25	0.05
0.85	11,533	4,401	0.28	590,224	15,386	100,691	7,265	0.32	0.07	0.14	0.03
0.90	6,109	2,733	0.31	596,333	9,277	103,424	4,532	0.33	0.04	0.09	0.02
0.95	4,085	1,888	0.32	600,418	5,192	105,312	2,644	0.34	0.02	0.05	0.01
1.00	5,192	2,644	0.34	605,610	0	107,956	0	nan	0.00	0.00	0.00

AdaBoost\_5\_Fold\_Easy\_Test\_Transformed\_95



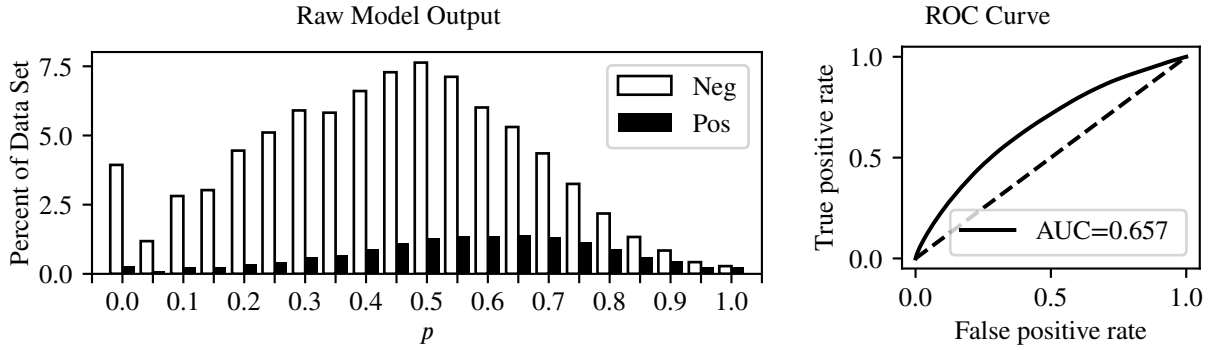
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	15,143	686	0.04	15,143	590,467	686	107,270	0.15	0.99	5.47	0.98
0.05	29,684	1,635	0.05	44,827	560,783	2,321	105,635	0.16	0.98	5.19	0.93
0.10	37,752	2,419	0.06	82,579	523,031	4,740	103,216	0.16	0.96	4.84	0.88
0.15	23,944	1,734	0.07	106,523	499,087	6,474	101,482	0.17	0.94	4.62	0.84
0.20	14,371	1,190	0.08	120,894	484,716	7,664	100,292	0.17	0.93	4.49	0.82
0.25	17,236	1,681	0.09	138,130	467,480	9,345	98,611	0.17	0.91	4.33	0.79
0.30	29,635	3,155	0.10	167,765	437,845	12,500	95,456	0.18	0.88	4.06	0.75
0.35	39,432	4,565	0.10	207,197	398,413	17,065	90,891	0.19	0.84	3.69	0.69
0.40	45,466	6,084	0.12	252,663	352,947	23,149	84,807	0.19	0.79	3.27	0.61
0.45	52,072	7,735	0.13	304,735	300,875	30,884	77,072	0.20	0.71	2.79	0.53
0.50	50,167	8,366	0.14	354,902	250,708	39,250	68,706	0.22	0.64	2.32	0.45
0.55	51,268	9,454	0.16	406,170	199,440	48,704	59,252	0.23	0.55	1.85	0.36
0.60	42,005	8,726	0.17	448,175	157,435	57,430	50,526	0.24	0.47	1.46	0.29
0.65	27,528	6,400	0.19	475,703	129,907	63,830	44,126	0.25	0.41	1.20	0.24
0.70	29,502	7,952	0.21	505,205	100,405	71,782	36,174	0.26	0.34	0.93	0.19
0.75	34,692	10,780	0.24	539,897	65,713	82,562	25,394	0.28	0.24	0.61	0.13
0.80	26,215	9,007	0.26	566,112	39,498	91,569	16,387	0.29	0.15	0.37	0.08
0.85	15,331	5,816	0.28	581,443	24,167	97,385	10,571	0.30	0.10	0.22	0.05
0.90	9,752	3,745	0.28	591,195	14,415	101,130	6,826	0.32	0.06	0.13	0.03
0.95	5,391	2,398	0.31	596,586	9,024	103,528	4,428	0.33	0.04	0.08	0.02
1.00	9,024	4,428	0.33	605,610	0	107,956	0	nan	0.00	0.00	0.00

BalBag\_5\_Fold\_Easy\_Test



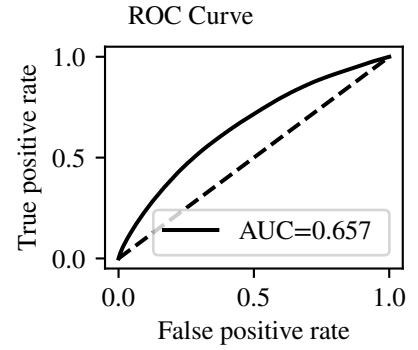
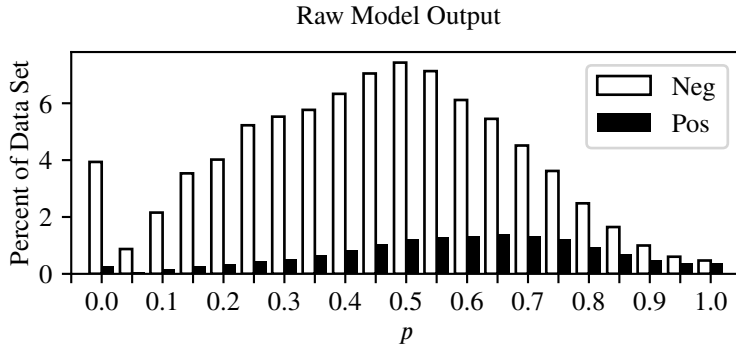
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	28,088	1,893	0.06	28,088	577,522	1,893	106,063	0.16	0.98	5.35	0.96
0.05	8,438	620	0.07	36,526	569,084	2,513	105,443	0.16	0.98	5.27	0.95
0.10	20,068	1,593	0.07	56,594	549,016	4,106	103,850	0.16	0.96	5.09	0.91
0.15	21,592	1,644	0.07	78,186	527,424	5,750	102,206	0.16	0.95	4.89	0.88
0.20	31,779	2,549	0.07	109,965	495,645	8,299	99,657	0.17	0.92	4.59	0.83
0.25	36,444	3,081	0.08	146,409	459,201	11,380	96,576	0.17	0.89	4.25	0.78
0.30	42,135	4,193	0.09	188,544	417,066	15,573	92,383	0.18	0.86	3.86	0.71
0.35	41,553	4,864	0.10	230,097	375,513	20,437	87,519	0.19	0.81	3.48	0.65
0.40	47,137	6,405	0.12	277,234	328,376	26,842	81,114	0.20	0.75	3.04	0.57
0.45	51,983	7,753	0.13	329,217	276,393	34,595	73,361	0.21	0.68	2.56	0.49
0.50	54,470	9,125	0.14	383,687	221,923	43,720	64,236	0.22	0.60	2.06	0.40
0.55	50,803	9,718	0.16	434,490	171,120	53,438	54,518	0.24	0.51	1.59	0.32
0.60	42,897	9,716	0.18	477,387	128,223	63,154	44,802	0.26	0.42	1.19	0.24
0.65	37,863	10,011	0.21	515,250	90,360	73,165	34,791	0.28	0.32	0.84	0.18
0.70	31,060	9,527	0.23	546,310	59,300	82,692	25,264	0.30	0.23	0.55	0.12
0.75	23,194	8,011	0.26	569,504	36,106	90,703	17,253	0.32	0.16	0.33	0.07
0.80	15,562	6,208	0.29	585,066	20,544	96,911	11,045	0.35	0.10	0.19	0.04
0.85	9,512	4,276	0.31	594,578	11,032	101,187	6,769	0.38	0.06	0.10	0.02
0.90	6,018	3,274	0.35	600,596	5,014	104,461	3,495	0.41	0.03	0.05	0.01
0.95	3,023	1,791	0.37	603,619	1,991	106,252	1,704	0.46	0.02	0.02	0.01
1.00	1,991	1,704	0.46	605,610	0	107,956	0	nan	0.00	0.00	0.00

BalBag\_5\_Fold\_Easy\_Test\_Transformed\_100



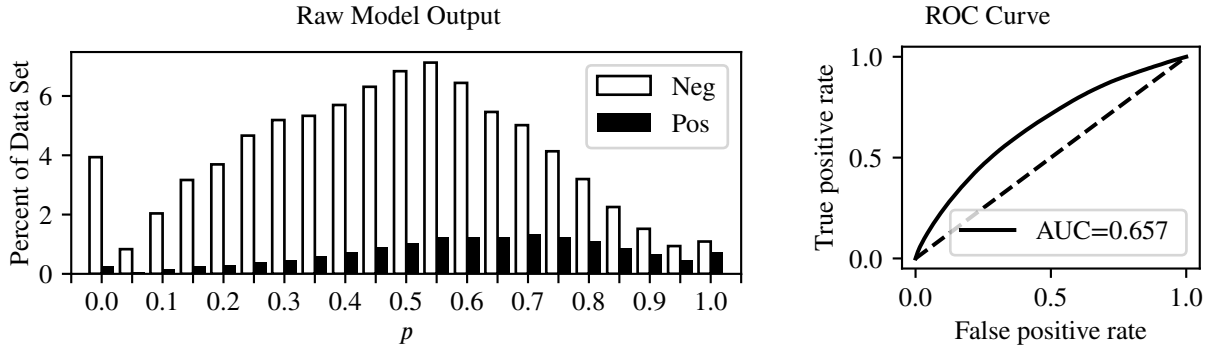
	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
p											
0.00	28,088	1,893	0.06	28,088	577,522	1,893	106,063	0.16	0.98	5.35	0.96
0.05	8,438	620	0.07	36,526	569,084	2,513	105,443	0.16	0.98	5.27	0.95
0.10	20,068	1,593	0.07	56,594	549,016	4,106	103,850	0.16	0.96	5.09	0.91
0.15	21,592	1,644	0.07	78,186	527,424	5,750	102,206	0.16	0.95	4.89	0.88
0.20	31,779	2,549	0.07	109,965	495,645	8,299	99,657	0.17	0.92	4.59	0.83
0.25	36,444	3,081	0.08	146,409	459,201	11,380	96,576	0.17	0.89	4.25	0.78
0.30	42,135	4,193	0.09	188,544	417,066	15,573	92,383	0.18	0.86	3.86	0.71
0.35	41,553	4,864	0.10	230,097	375,513	20,437	87,519	0.19	0.81	3.48	0.65
0.40	47,137	6,405	0.12	277,234	328,376	26,842	81,114	0.20	0.75	3.04	0.57
0.45	51,983	7,753	0.13	329,217	276,393	34,595	73,361	0.21	0.68	2.56	0.49
0.50	54,470	9,125	0.14	383,687	221,923	43,720	64,236	0.22	0.60	2.06	0.40
0.55	50,803	9,718	0.16	434,490	171,120	53,438	54,518	0.24	0.51	1.59	0.32
0.60	42,897	9,716	0.18	477,387	128,223	63,154	44,802	0.26	0.42	1.19	0.24
0.65	37,863	10,011	0.21	515,250	90,360	73,165	34,791	0.28	0.32	0.84	0.18
0.70	31,060	9,527	0.23	546,310	59,300	82,692	25,264	0.30	0.23	0.55	0.12
0.75	23,194	8,011	0.26	569,504	36,106	90,703	17,253	0.32	0.16	0.33	0.07
0.80	15,562	6,208	0.29	585,066	20,544	96,911	11,045	0.35	0.10	0.19	0.04
0.85	9,512	4,276	0.31	594,578	11,032	101,187	6,769	0.38	0.06	0.10	0.02
0.90	6,018	3,274	0.35	600,596	5,014	104,461	3,495	0.41	0.03	0.05	0.01
0.95	3,023	1,791	0.37	603,619	1,991	106,252	1,704	0.46	0.02	0.02	0.01
1.00	1,991	1,704	0.46	605,610	0	107,956	0	nan	0.00	0.00	0.00

BalBag\_5\_Fold\_Easy\_Test\_Transformed\_98



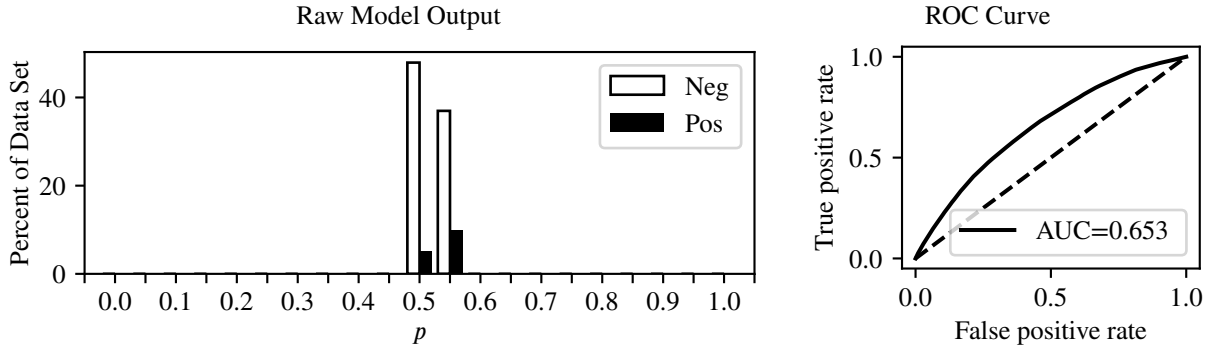
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	28,088	1,893	0.06	28,088	577,522	1,893	106,063	0.16	0.98	5.35	0.96
0.05	6,231	437	0.07	34,319	571,291	2,330	105,626	0.16	0.98	5.29	0.95
0.10	15,375	1,162	0.07	49,694	555,916	3,492	104,464	0.16	0.97	5.15	0.93
0.15	25,220	1,943	0.07	74,914	530,696	5,435	102,521	0.16	0.95	4.92	0.89
0.20	28,674	2,271	0.07	103,588	502,022	7,706	100,250	0.17	0.93	4.65	0.84
0.25	37,287	3,197	0.08	140,875	464,735	10,903	97,053	0.17	0.90	4.30	0.79
0.30	39,449	3,750	0.09	180,324	425,286	14,653	93,303	0.18	0.86	3.94	0.73
0.35	41,152	4,657	0.10	221,476	384,134	19,310	88,646	0.19	0.82	3.56	0.66
0.40	45,174	5,979	0.12	266,650	338,960	25,289	82,667	0.20	0.77	3.14	0.59
0.45	50,283	7,370	0.13	316,933	288,677	32,659	75,297	0.21	0.70	2.67	0.51
0.50	53,016	8,674	0.14	369,949	235,661	41,333	66,623	0.22	0.62	2.18	0.42
0.55	50,879	9,260	0.15	420,828	184,782	50,593	57,363	0.24	0.53	1.71	0.34
0.60	43,632	9,379	0.18	464,460	141,150	59,972	47,984	0.25	0.44	1.31	0.27
0.65	38,900	9,890	0.20	503,360	102,250	69,862	38,094	0.27	0.35	0.95	0.20
0.70	32,211	9,406	0.23	535,571	70,039	79,268	28,688	0.29	0.27	0.65	0.14
0.75	25,823	8,556	0.25	561,394	44,216	87,824	20,132	0.31	0.19	0.41	0.09
0.80	17,702	6,644	0.27	579,096	26,514	94,468	13,488	0.34	0.12	0.25	0.06
0.85	11,750	5,008	0.30	590,846	14,764	99,476	8,480	0.36	0.08	0.14	0.03
0.90	7,116	3,359	0.32	597,962	7,648	102,835	5,121	0.40	0.05	0.07	0.02
0.95	4,300	2,574	0.37	602,262	3,348	105,409	2,547	0.43	0.02	0.03	0.01
1.00	3,348	2,547	0.43	605,610	0	107,956	0	nan	0.00	0.00	0.00

BalBag\_5\_Fold\_Easy\_Test\_Transformed\_95



$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	28,088	1,893	0.06	28,088	577,522	1,893	106,063	0.16	0.98	5.35	0.96
0.05	5,943	423	0.07	34,031	571,579	2,316	105,640	0.16	0.98	5.29	0.95
0.10	14,546	1,090	0.07	48,577	557,033	3,406	104,550	0.16	0.97	5.16	0.93
0.15	22,594	1,728	0.07	71,171	534,439	5,134	102,822	0.16	0.95	4.95	0.89
0.20	26,349	2,094	0.07	97,520	508,090	7,228	100,728	0.17	0.93	4.71	0.85
0.25	33,277	2,788	0.08	130,797	474,813	10,016	97,940	0.17	0.91	4.40	0.80
0.30	37,024	3,322	0.08	167,821	437,789	13,338	94,618	0.18	0.88	4.06	0.75
0.35	38,037	4,134	0.10	205,858	399,752	17,472	90,484	0.18	0.84	3.70	0.69
0.40	40,647	5,055	0.11	246,505	359,105	22,527	85,429	0.19	0.79	3.33	0.62
0.45	45,025	6,437	0.13	291,530	314,080	28,964	78,992	0.20	0.73	2.91	0.55
0.50	48,781	7,328	0.13	340,311	265,299	36,292	71,664	0.21	0.66	2.46	0.47
0.55	50,850	8,750	0.15	391,161	214,449	45,042	62,914	0.23	0.58	1.99	0.39
0.60	45,963	8,901	0.16	437,124	168,486	53,943	54,013	0.24	0.50	1.56	0.31
0.65	38,971	8,859	0.19	476,095	129,515	62,802	45,154	0.26	0.42	1.20	0.24
0.70	35,793	9,442	0.21	511,888	93,722	72,244	35,712	0.28	0.33	0.87	0.18
0.75	29,505	8,857	0.23	541,393	64,217	81,101	26,855	0.29	0.25	0.59	0.13
0.80	22,815	7,722	0.25	564,208	41,402	88,823	19,133	0.32	0.18	0.38	0.08
0.85	16,088	6,164	0.28	580,296	25,314	94,987	12,969	0.34	0.12	0.23	0.05
0.90	10,844	4,614	0.30	591,140	14,470	99,601	8,355	0.37	0.08	0.13	0.03
0.95	6,689	3,191	0.32	597,829	7,781	102,792	5,164	0.40	0.05	0.07	0.02
1.00	7,781	5,164	0.40	605,610	0	107,956	0	nan	0.00	0.00	0.00

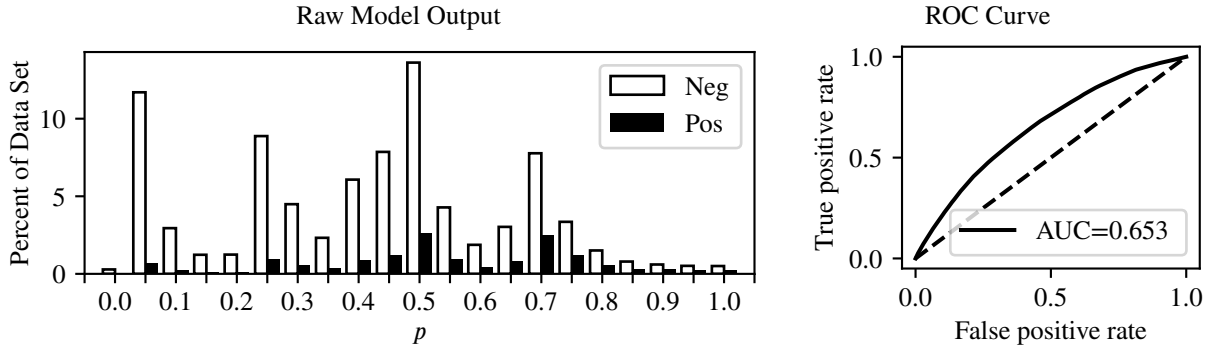
EEC\_5\_Fold\_Easy\_Test



$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.05	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.10	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.15	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.20	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.25	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.30	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.35	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.40	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.45	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.50	341,856	37,087	0.10	341,856	263,754	37,087	70,869	0.21	0.66	2.44	0.47
0.55	263,754	70,869	0.21	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.60	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.65	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.70	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.75	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.80	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.85	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.90	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.95	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
1.00	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00

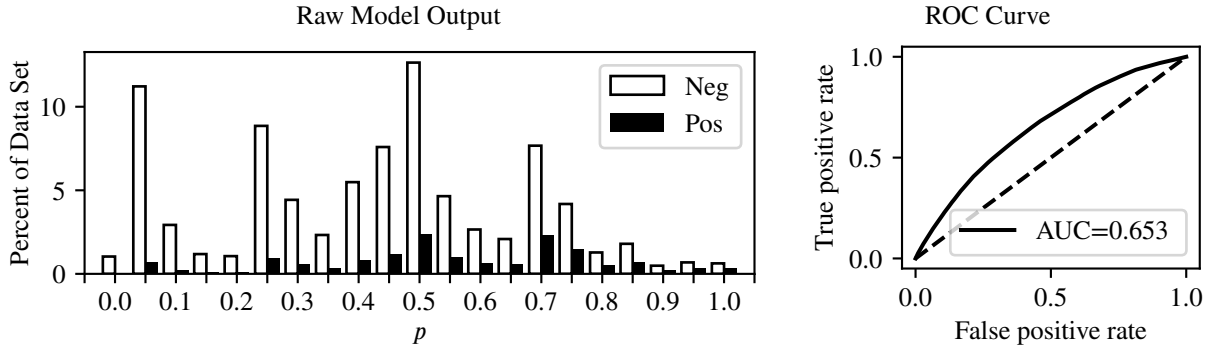


EEC\_5\_Fold\_Easy\_Test\_Transformed\_100



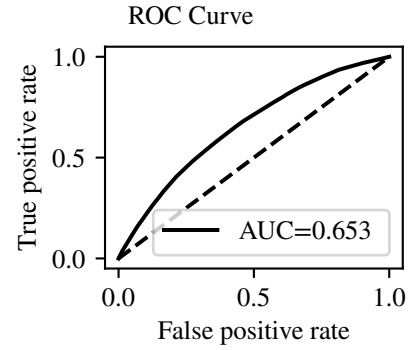
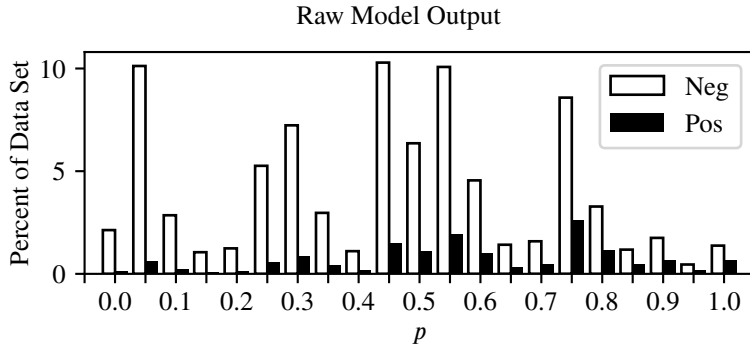
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	2,029	124	0.06	2,029	603,581	124	107,832	0.15	1.00	5.59	1.00
0.05	83,494	4,875	0.06	85,523	520,087	4,999	102,957	0.17	0.95	4.82	0.87
0.10	21,019	1,490	0.07	106,542	499,068	6,489	101,467	0.17	0.94	4.62	0.84
0.15	8,774	674	0.07	115,316	490,294	7,163	100,793	0.17	0.93	4.54	0.83
0.20	8,856	872	0.09	124,172	481,438	8,035	99,921	0.17	0.93	4.46	0.81
0.25	63,358	6,766	0.10	187,530	418,080	14,801	93,155	0.18	0.86	3.87	0.72
0.30	32,038	4,042	0.11	219,568	386,042	18,843	89,113	0.19	0.83	3.58	0.67
0.35	16,576	2,356	0.12	236,144	369,466	21,199	86,757	0.19	0.80	3.42	0.64
0.40	43,338	6,297	0.13	279,482	326,128	27,496	80,460	0.20	0.75	3.02	0.57
0.45	56,084	8,486	0.13	335,566	270,044	35,982	71,974	0.21	0.67	2.50	0.48
0.50	97,154	18,428	0.16	432,720	172,890	54,410	53,546	0.24	0.50	1.60	0.32
0.55	30,556	6,699	0.18	463,276	142,334	61,109	46,847	0.25	0.43	1.32	0.27
0.60	13,350	3,103	0.19	476,626	128,984	64,212	43,744	0.25	0.41	1.19	0.24
0.65	21,604	5,958	0.22	498,230	107,380	70,170	37,786	0.26	0.35	0.99	0.20
0.70	55,456	17,517	0.24	553,686	51,924	87,687	20,269	0.28	0.19	0.48	0.10
0.75	23,924	8,625	0.26	577,610	28,000	96,312	11,644	0.29	0.11	0.26	0.06
0.80	10,758	3,880	0.27	588,368	17,242	100,192	7,764	0.31	0.07	0.16	0.04
0.85	5,654	2,299	0.29	594,022	11,588	102,491	5,465	0.32	0.05	0.11	0.02
0.90	4,304	1,951	0.31	598,326	7,284	104,442	3,514	0.33	0.03	0.07	0.02
0.95	3,683	1,693	0.31	602,009	3,601	106,135	1,821	0.34	0.02	0.03	0.01
1.00	3,601	1,821	0.34	605,610	0	107,956	0	nan	0.00	0.00	0.00

EEC\_5\_Fold\_Easy\_Test\_Transformed\_98



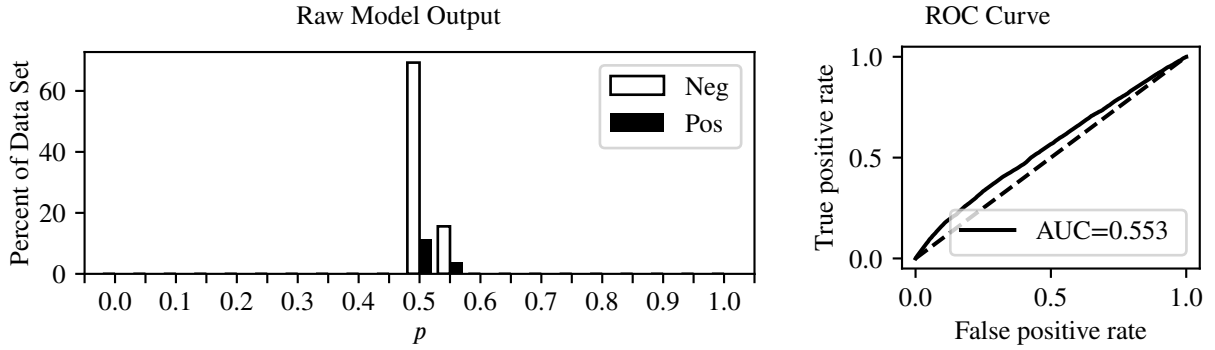
$\hat{p}$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	7,395	411	0.05	7,395	598,215	411	107,545	0.15	1.00	5.54	0.99
0.05	80,045	4,713	0.06	87,440	518,170	5,124	102,832	0.17	0.95	4.80	0.87
0.10	20,895	1,507	0.07	108,335	497,275	6,631	101,325	0.17	0.94	4.61	0.84
0.15	8,446	668	0.07	116,781	488,829	7,299	100,657	0.17	0.93	4.53	0.83
0.20	7,568	757	0.09	124,349	481,261	8,056	99,900	0.17	0.93	4.46	0.81
0.25	63,181	6,745	0.10	187,530	418,080	14,801	93,155	0.18	0.86	3.87	0.72
0.30	31,602	3,963	0.11	219,132	386,478	18,764	89,192	0.19	0.83	3.58	0.67
0.35	16,600	2,343	0.12	235,732	369,878	21,107	86,849	0.19	0.80	3.43	0.64
0.40	39,160	5,651	0.13	274,892	330,718	26,758	81,198	0.20	0.75	3.06	0.58
0.45	54,156	8,114	0.13	329,048	276,562	34,872	73,084	0.21	0.68	2.56	0.49
0.50	90,205	16,747	0.16	419,253	186,357	51,619	56,337	0.23	0.52	1.73	0.34
0.55	33,169	7,092	0.18	452,422	153,188	58,711	49,245	0.24	0.46	1.42	0.28
0.60	18,939	4,290	0.18	471,361	134,249	63,001	44,955	0.25	0.42	1.24	0.25
0.65	14,872	3,897	0.21	486,233	119,377	66,898	41,058	0.26	0.38	1.11	0.22
0.70	54,729	16,351	0.23	540,962	64,648	83,249	24,707	0.28	0.23	0.60	0.13
0.75	29,834	10,372	0.26	570,796	34,814	93,621	14,335	0.29	0.13	0.32	0.07
0.80	9,134	3,495	0.28	579,930	25,680	97,116	10,840	0.30	0.10	0.24	0.05
0.85	12,833	4,943	0.28	592,763	12,847	102,059	5,897	0.31	0.05	0.12	0.03
0.90	3,482	1,440	0.29	596,245	9,365	103,499	4,457	0.32	0.04	0.09	0.02
0.95	4,888	2,210	0.31	601,133	4,477	105,709	2,247	0.33	0.02	0.04	0.01
1.00	4,477	2,247	0.33	605,610	0	107,956	0	nan	0.00	0.00	0.00

EEC\_5\_Fold\_Easy\_Test\_Transformed\_95



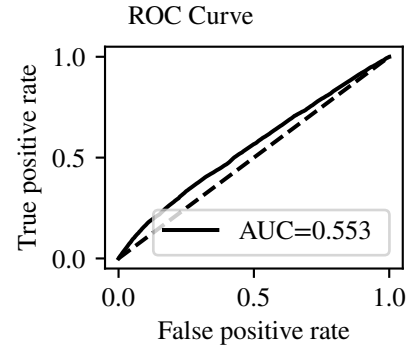
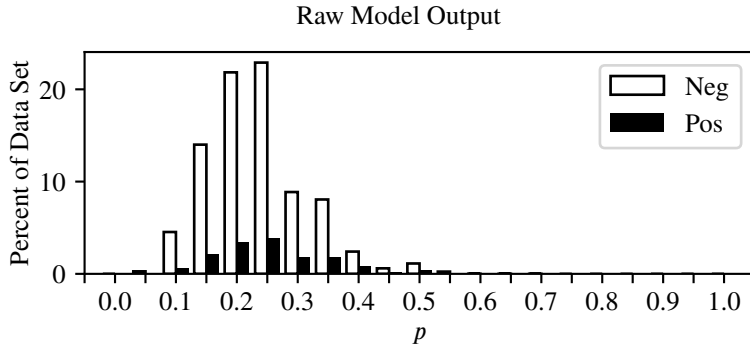
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	15,208	879	0.05	15,208	590,402	879	107,077	0.15	0.99	5.47	0.98
0.05	72,232	4,245	0.06	87,440	518,170	5,124	102,832	0.17	0.95	4.80	0.87
0.10	20,359	1,472	0.07	107,799	497,811	6,596	101,360	0.17	0.94	4.61	0.84
0.15	7,517	567	0.07	115,316	490,294	7,163	100,793	0.17	0.93	4.54	0.83
0.20	8,856	872	0.09	124,172	481,438	8,035	99,921	0.17	0.93	4.46	0.81
0.25	37,541	3,970	0.10	161,713	443,897	12,005	95,951	0.18	0.89	4.11	0.76
0.30	51,613	5,945	0.10	213,326	392,284	17,950	90,006	0.19	0.83	3.63	0.68
0.35	21,190	2,912	0.12	234,516	371,094	20,862	87,094	0.19	0.81	3.44	0.64
0.40	7,885	1,295	0.14	242,401	363,209	22,157	85,799	0.19	0.79	3.36	0.63
0.45	73,409	10,688	0.13	315,810	289,800	32,845	75,111	0.21	0.70	2.68	0.51
0.50	45,375	7,764	0.15	361,185	244,425	40,609	67,347	0.22	0.62	2.26	0.44
0.55	71,900	13,894	0.16	433,085	172,525	54,503	53,453	0.24	0.50	1.60	0.32
0.60	32,481	7,148	0.18	465,566	140,044	61,651	46,305	0.25	0.43	1.30	0.26
0.65	10,118	2,349	0.19	475,684	129,926	64,000	43,956	0.25	0.41	1.20	0.24
0.70	11,317	3,159	0.22	487,001	118,609	67,159	40,797	0.26	0.38	1.10	0.22
0.75	61,236	18,598	0.23	548,237	57,373	85,757	22,199	0.28	0.21	0.53	0.11
0.80	23,396	8,208	0.26	571,633	33,977	93,965	13,991	0.29	0.13	0.31	0.07
0.85	8,417	3,199	0.28	580,050	25,560	97,164	10,792	0.30	0.10	0.24	0.05
0.90	12,498	4,803	0.28	592,548	13,062	101,967	5,989	0.31	0.06	0.12	0.03
0.95	3,248	1,326	0.29	595,796	9,814	103,293	4,663	0.32	0.04	0.09	0.02
1.00	9,814	4,663	0.32	605,610	0	107,956	0	nan	0.00	0.00	0.00

RUSBoost\_5\_Fold\_Easy\_Test



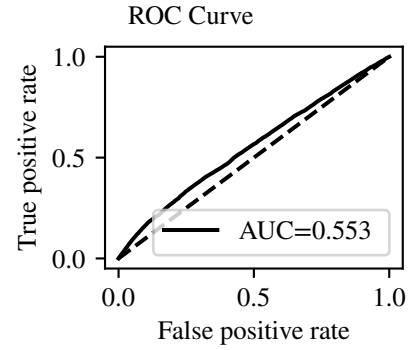
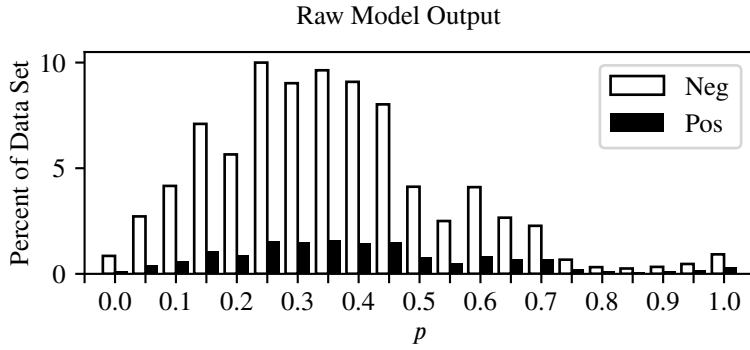
	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
p											
0.00	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.05	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.10	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.15	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.20	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.25	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.30	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.35	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.40	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.45	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.50	494,427	79,936	0.14	494,427	111,183	79,936	28,020	0.20	0.26	1.03	0.20
0.55	111,183	28,020	0.20	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.60	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.65	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.70	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.75	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.80	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.85	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.90	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.95	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
1.00	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00

RUSBoost\_5\_Fold\_Easy\_Test\_Transformed\_100



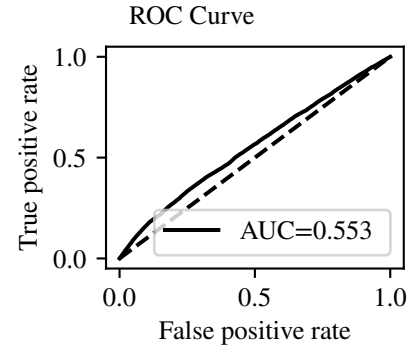
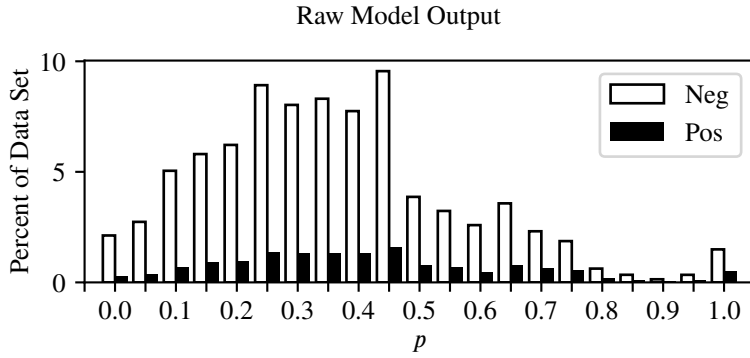
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	1	0	0.00	1	605,609	0	107,956	0.15	1.00	5.61	1.00
0.05	1,936	276	0.12	1,937	603,673	276	107,680	0.15	1.00	5.59	1.00
0.10	32,366	4,548	0.12	34,303	571,307	4,824	103,132	0.15	0.96	5.29	0.95
0.15	99,935	15,264	0.13	134,238	471,372	20,088	87,868	0.16	0.81	4.37	0.78
0.20	155,836	24,518	0.14	290,074	315,536	44,606	63,350	0.17	0.59	2.92	0.53
0.25	163,386	27,180	0.14	453,460	152,150	71,786	36,170	0.19	0.34	1.41	0.26
0.30	63,274	13,016	0.17	516,734	88,876	84,802	23,154	0.21	0.21	0.82	0.16
0.35	57,518	12,951	0.18	574,252	31,358	97,753	10,203	0.25	0.09	0.29	0.06
0.40	17,229	5,582	0.24	591,481	14,129	103,335	4,621	0.25	0.04	0.13	0.03
0.45	4,271	1,321	0.24	595,752	9,858	104,656	3,300	0.25	0.03	0.09	0.02
0.50	8,020	2,641	0.25	603,772	1,838	107,297	659	0.26	0.01	0.02	0.00
0.55	1,740	618	0.26	605,512	98	107,915	41	0.29	0.00	0.00	0.00
0.60	44	26	0.37	605,556	54	107,941	15	0.22	0.00	0.00	0.00
0.65	42	13	0.24	605,598	12	107,954	2	0.14	0.00	0.00	0.00
0.70	3	0	0.00	605,601	9	107,954	2	0.18	0.00	0.00	0.00
0.75	1	0	0.00	605,602	8	107,954	2	0.20	0.00	0.00	0.00
0.80	2	0	0.00	605,604	6	107,954	2	0.25	0.00	0.00	0.00
0.85	2	0	0.00	605,606	4	107,954	2	0.33	0.00	0.00	0.00
0.90	1	0	0.00	605,607	3	107,954	2	0.40	0.00	0.00	0.00
0.95	1	1	0.50	605,608	2	107,955	1	0.33	0.00	0.00	0.00
1.00	2	1	0.33	605,610	0	107,956	0	nan	0.00	0.00	0.00

RUSBoost\_5\_Fold\_Easy\_Test\_Transformed\_98



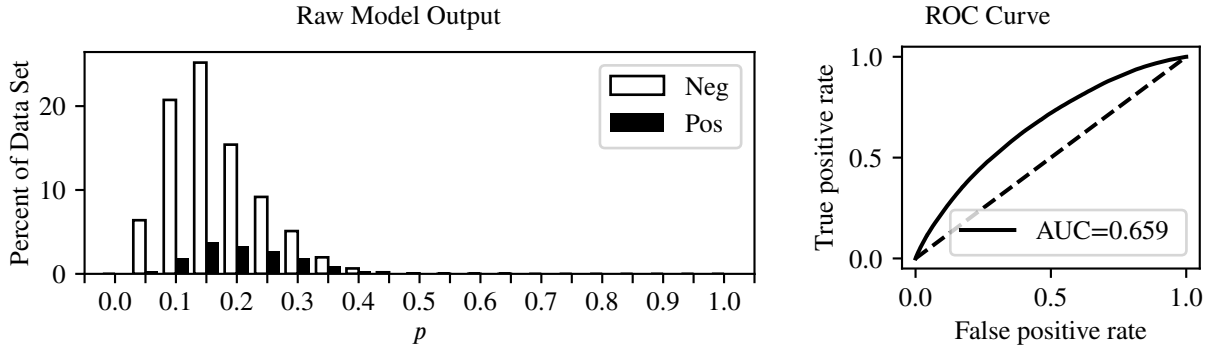
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	6,062	739	0.11	6,062	599,548	739	107,217	0.15	0.99	5.55	0.99
0.05	19,404	2,807	0.13	25,466	580,144	3,546	104,410	0.15	0.97	5.37	0.96
0.10	29,700	4,208	0.12	55,166	550,444	7,754	100,202	0.15	0.93	5.10	0.91
0.15	50,647	7,694	0.13	105,813	499,797	15,448	92,508	0.16	0.86	4.63	0.83
0.20	40,335	6,386	0.14	146,148	459,462	21,834	86,122	0.16	0.80	4.26	0.76
0.25	71,348	10,875	0.13	217,496	388,114	32,709	75,247	0.16	0.70	3.60	0.65
0.30	64,387	10,542	0.14	281,883	323,727	43,251	64,705	0.17	0.60	3.00	0.54
0.35	68,755	11,479	0.14	350,638	254,972	54,730	53,226	0.17	0.49	2.36	0.43
0.40	64,848	10,453	0.14	415,486	190,124	65,183	42,773	0.18	0.40	1.76	0.33
0.45	57,243	10,757	0.16	472,729	132,881	75,940	32,016	0.19	0.30	1.23	0.23
0.50	29,422	5,646	0.16	502,151	103,459	81,586	26,370	0.20	0.24	0.96	0.18
0.55	17,843	3,627	0.17	519,994	85,616	85,213	22,743	0.21	0.21	0.79	0.15
0.60	29,283	5,919	0.17	549,277	56,333	91,132	16,824	0.23	0.16	0.52	0.10
0.65	18,969	5,019	0.21	568,246	37,364	96,151	11,805	0.24	0.11	0.35	0.07
0.70	16,226	4,851	0.23	584,472	21,138	101,002	6,954	0.25	0.06	0.20	0.04
0.75	4,782	1,562	0.25	589,254	16,356	102,564	5,392	0.25	0.05	0.15	0.03
0.80	2,263	787	0.26	591,517	14,093	103,351	4,605	0.25	0.04	0.13	0.03
0.85	1,810	593	0.25	593,327	12,283	103,944	4,012	0.25	0.04	0.11	0.02
0.90	2,355	677	0.22	595,682	9,928	104,621	3,335	0.25	0.03	0.09	0.02
0.95	3,339	1,058	0.24	599,021	6,589	105,679	2,277	0.26	0.02	0.06	0.01
1.00	6,589	2,277	0.26	605,610	0	107,956	0	nan	0.00	0.00	0.00

RUSBoost\_5\_Fold\_Easy\_Test\_Transformed\_95



	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
p											
0.00	15,142	2,077	0.12	15,142	590,468	2,077	105,879	0.15	0.98	5.47	0.98
0.05	19,532	2,834	0.13	34,674	570,936	4,911	103,045	0.15	0.95	5.29	0.94
0.10	36,019	4,906	0.12	70,693	534,917	9,817	98,139	0.16	0.91	4.95	0.89
0.15	41,414	6,667	0.14	112,107	493,503	16,484	91,472	0.16	0.85	4.57	0.82
0.20	44,365	6,790	0.13	156,472	449,138	23,274	84,682	0.16	0.78	4.16	0.75
0.25	63,646	9,869	0.13	220,118	385,492	33,143	74,813	0.16	0.69	3.57	0.65
0.30	57,278	9,534	0.14	277,396	328,214	42,677	65,279	0.17	0.60	3.04	0.55
0.35	59,274	9,524	0.14	336,670	268,940	52,201	55,755	0.17	0.52	2.49	0.46
0.40	55,281	9,509	0.15	391,951	213,659	61,710	46,246	0.18	0.43	1.98	0.36
0.45	68,180	11,533	0.14	460,131	145,479	73,243	34,713	0.19	0.32	1.35	0.25
0.50	27,599	5,470	0.17	487,730	117,880	78,713	29,243	0.20	0.27	1.09	0.21
0.55	23,060	4,846	0.17	510,790	94,820	83,559	24,397	0.20	0.23	0.88	0.17
0.60	18,484	3,287	0.15	529,274	76,336	86,846	21,110	0.22	0.20	0.71	0.14
0.65	25,507	5,727	0.18	554,781	50,829	92,573	15,383	0.23	0.14	0.47	0.09
0.70	16,499	4,452	0.21	571,280	34,330	97,025	10,931	0.24	0.10	0.32	0.06
0.75	13,325	4,032	0.23	584,605	21,005	101,057	6,899	0.25	0.06	0.19	0.04
0.80	4,451	1,458	0.25	589,056	16,554	102,515	5,441	0.25	0.05	0.15	0.03
0.85	2,453	834	0.25	591,509	14,101	103,349	4,607	0.25	0.04	0.13	0.03
0.90	1,003	270	0.21	592,512	13,098	103,619	4,337	0.25	0.04	0.12	0.02
0.95	2,441	810	0.25	594,953	10,657	104,429	3,527	0.25	0.03	0.10	0.02
1.00	10,657	3,527	0.25	605,610	0	107,956	0	nan	0.00	0.00	0.00

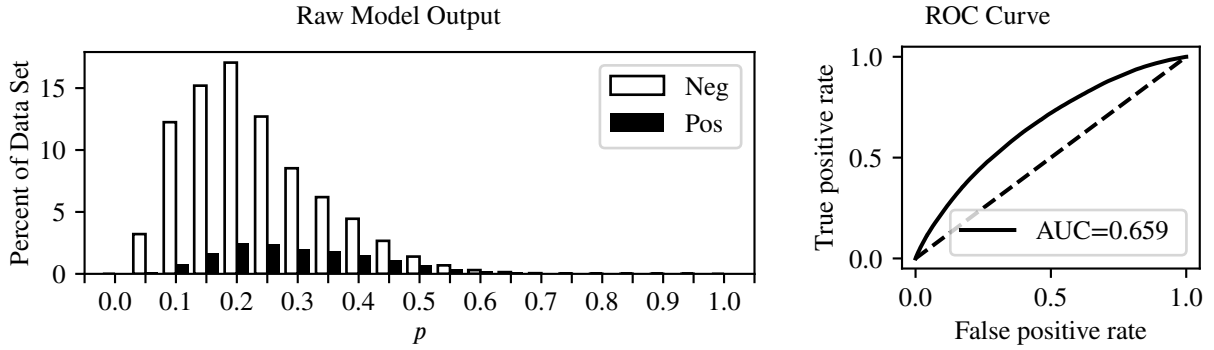
KBFC\_5\_Fold\_alpha\_0\_5\_gamma\_0\_0\_Easy\_Test



	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
$p$											
0.00	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.05	45,635	2,149	0.04	45,635	559,975	2,149	105,807	0.16	0.98	5.19	0.93
0.10	147,990	13,150	0.08	193,625	411,985	15,299	92,657	0.18	0.86	3.82	0.71
0.15	179,745	26,552	0.13	373,370	232,240	41,851	66,105	0.22	0.61	2.15	0.42
0.20	109,952	23,344	0.18	483,322	122,288	65,195	42,761	0.26	0.40	1.13	0.23
0.25	65,458	19,106	0.23	548,780	56,830	84,301	23,655	0.29	0.22	0.53	0.11
0.30	36,408	13,523	0.27	585,188	20,422	97,824	10,132	0.33	0.09	0.19	0.04
0.35	14,069	6,559	0.32	599,257	6,353	104,383	3,573	0.36	0.03	0.06	0.01
0.40	4,612	2,498	0.35	603,869	1,741	106,881	1,075	0.38	0.01	0.02	0.00
0.45	1,329	799	0.38	605,198	412	107,680	276	0.40	0.00	0.00	0.00
0.50	347	232	0.40	605,545	65	107,912	44	0.40	0.00	0.00	0.00
0.55	54	28	0.34	605,599	11	107,940	16	0.59	0.00	0.00	0.00
0.60	7	13	0.65	605,606	4	107,953	3	0.43	0.00	0.00	0.00
0.65	3	2	0.40	605,609	1	107,955	1	0.50	0.00	0.00	0.00
0.70	0	1	1.00	605,609	1	107,956	0	0.00	0.00	0.00	0.00
0.75	1	0	0.00	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.80	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.85	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.90	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
0.95	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00
1.00	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00

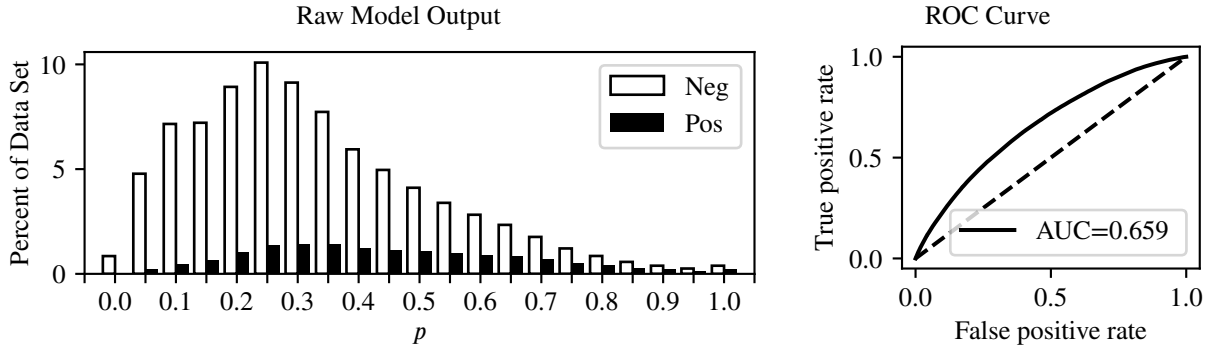


KBFC\_5\_Fold\_alpha\_0\_5\_gamma\_0\_0\_Easy\_Test\_Transformed\_100



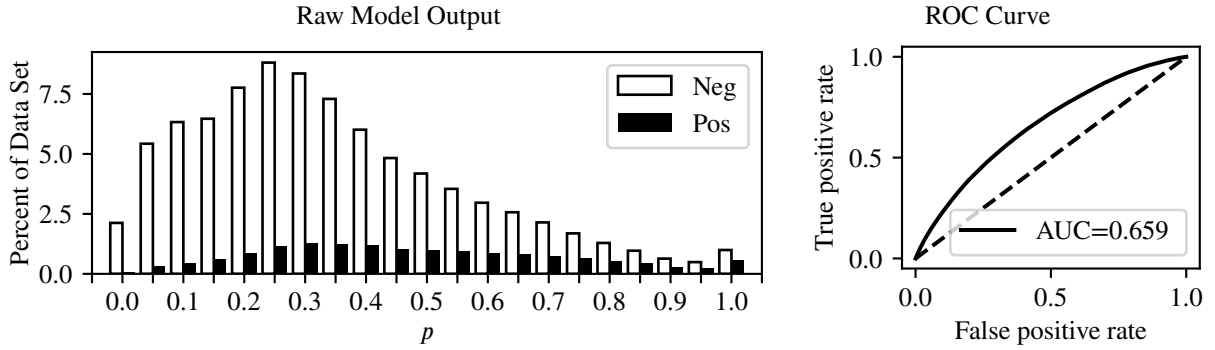
	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
p											
0.00	1	0	0.00	1	605,609	0	107,956	0.15	1.00	5.61	1.00
0.05	22,907	929	0.04	22,908	582,702	929	107,027	0.16	0.99	5.40	0.97
0.10	87,400	5,712	0.06	110,308	495,302	6,641	101,315	0.17	0.94	4.59	0.84
0.15	108,453	11,816	0.10	218,761	386,849	18,457	89,499	0.19	0.83	3.58	0.67
0.20	121,735	17,716	0.13	340,496	265,114	36,173	71,783	0.21	0.66	2.46	0.47
0.25	90,654	17,126	0.16	431,150	174,460	53,299	54,657	0.24	0.51	1.62	0.32
0.30	60,848	14,126	0.19	491,998	113,612	67,425	40,531	0.26	0.38	1.05	0.22
0.35	44,215	12,881	0.23	536,213	69,397	80,306	27,650	0.28	0.26	0.64	0.14
0.40	31,746	10,680	0.25	567,959	37,651	90,986	16,970	0.31	0.16	0.35	0.08
0.45	19,018	7,644	0.29	586,977	18,633	98,630	9,326	0.33	0.09	0.17	0.04
0.50	9,955	4,632	0.32	596,932	8,678	103,262	4,694	0.35	0.04	0.08	0.02
0.55	4,905	2,476	0.34	601,837	3,773	105,738	2,218	0.37	0.02	0.03	0.01
0.60	2,168	1,209	0.36	604,005	1,605	106,947	1,009	0.39	0.01	0.01	0.00
0.65	1,003	631	0.39	605,008	602	107,578	378	0.39	0.00	0.01	0.00
0.70	385	242	0.39	605,393	217	107,820	136	0.39	0.00	0.00	0.00
0.75	157	92	0.37	605,550	60	107,912	44	0.42	0.00	0.00	0.00
0.80	40	21	0.34	605,590	20	107,933	23	0.53	0.00	0.00	0.00
0.85	11	10	0.48	605,601	9	107,943	13	0.59	0.00	0.00	0.00
0.90	5	10	0.67	605,606	4	107,953	3	0.43	0.00	0.00	0.00
0.95	3	2	0.40	605,609	1	107,955	1	0.50	0.00	0.00	0.00
1.00	1	1	0.50	605,610	0	107,956	0	nan	0.00	0.00	0.00

KBFC\_5\_Fold\_alpha\_0\_5\_gamma\_0\_0\_Easy\_Test\_Transformed\_98



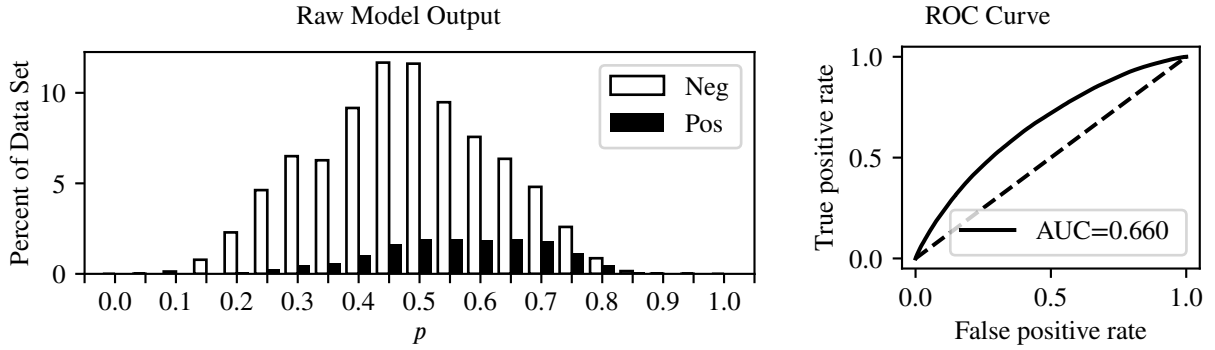
	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
p											
0.00	6,057	178	0.03	6,057	599,553	178	107,778	0.15	1.00	5.55	0.99
0.05	34,111	1,645	0.05	40,168	565,442	1,823	106,133	0.16	0.98	5.24	0.94
0.10	51,065	3,291	0.06	91,233	514,377	5,114	102,842	0.17	0.95	4.76	0.86
0.15	51,467	4,556	0.08	142,700	462,910	9,670	98,286	0.18	0.91	4.29	0.79
0.20	63,695	7,255	0.10	206,395	399,215	16,925	91,031	0.19	0.84	3.70	0.69
0.25	71,964	9,552	0.12	278,359	327,251	26,477	81,479	0.20	0.75	3.03	0.57
0.30	65,152	10,211	0.14	343,511	262,099	36,688	71,268	0.21	0.66	2.43	0.47
0.35	55,164	10,003	0.15	398,675	206,935	46,691	61,265	0.23	0.57	1.92	0.38
0.40	42,418	8,752	0.17	441,093	164,517	55,443	52,513	0.24	0.49	1.52	0.30
0.45	35,403	7,991	0.18	476,496	129,114	63,434	44,522	0.26	0.41	1.20	0.24
0.50	29,331	7,796	0.21	505,827	99,783	71,230	36,726	0.27	0.34	0.92	0.19
0.55	24,192	7,142	0.23	530,019	75,591	78,372	29,584	0.28	0.27	0.70	0.15
0.60	20,135	6,379	0.24	550,154	55,456	84,751	23,205	0.30	0.21	0.51	0.11
0.65	16,684	5,833	0.26	566,838	38,772	90,584	17,372	0.31	0.16	0.36	0.08
0.70	12,583	4,791	0.28	579,421	26,189	95,375	12,581	0.32	0.12	0.24	0.05
0.75	8,656	3,734	0.30	588,077	17,533	99,109	8,847	0.34	0.08	0.16	0.04
0.80	6,094	2,750	0.31	594,171	11,439	101,859	6,097	0.35	0.06	0.11	0.02
0.85	4,073	2,034	0.33	598,244	7,366	103,893	4,063	0.36	0.04	0.07	0.02
0.90	2,777	1,396	0.33	601,021	4,589	105,289	2,667	0.37	0.02	0.04	0.01
0.95	1,812	994	0.35	602,833	2,777	106,283	1,673	0.38	0.02	0.03	0.01
1.00	2,777	1,673	0.38	605,610	0	107,956	0	nan	0.00	0.00	0.00

KBFC\_5\_Fold\_alpha\_0\_5\_gamma\_0\_0\_Easy\_Test\_Transformed\_95



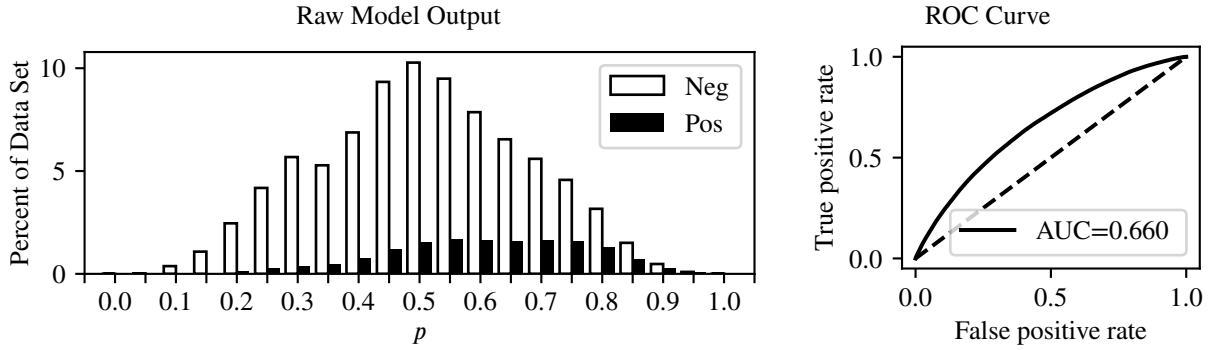
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	15,154	564	0.04	15,154	590,456	564	107,392	0.15	0.99	5.47	0.98
0.05	38,721	2,096	0.05	53,875	551,735	2,660	105,296	0.16	0.98	5.11	0.92
0.10	45,159	3,089	0.06	99,034	506,576	5,749	102,207	0.17	0.95	4.69	0.85
0.15	46,152	4,176	0.08	145,186	460,424	9,925	98,031	0.18	0.91	4.26	0.78
0.20	55,387	6,237	0.10	200,573	405,037	16,162	91,794	0.18	0.85	3.75	0.70
0.25	62,853	8,190	0.12	263,426	342,184	24,352	83,604	0.20	0.77	3.17	0.60
0.30	59,614	9,022	0.13	323,040	282,570	33,374	74,582	0.21	0.69	2.62	0.50
0.35	52,053	8,820	0.14	375,093	230,517	42,194	65,762	0.22	0.61	2.14	0.42
0.40	42,890	8,370	0.16	417,983	187,627	50,564	57,392	0.23	0.53	1.74	0.34
0.45	34,459	7,342	0.18	452,442	153,168	57,906	50,050	0.25	0.46	1.42	0.28
0.50	29,852	7,038	0.19	482,294	123,316	64,944	43,012	0.26	0.40	1.14	0.23
0.55	25,280	6,811	0.21	507,574	98,036	71,755	36,201	0.27	0.34	0.91	0.19
0.60	21,159	6,231	0.23	528,733	76,877	77,986	29,970	0.28	0.28	0.71	0.15
0.65	18,328	5,790	0.24	547,061	58,549	83,776	24,180	0.29	0.22	0.54	0.12
0.70	15,304	5,238	0.25	562,365	43,245	89,014	18,942	0.30	0.18	0.40	0.09
0.75	12,049	4,506	0.27	574,414	31,196	93,520	14,436	0.32	0.13	0.29	0.06
0.80	9,194	3,636	0.28	583,608	22,002	97,156	10,800	0.33	0.10	0.20	0.05
0.85	6,885	3,073	0.31	590,493	15,117	100,229	7,727	0.34	0.07	0.14	0.03
0.90	4,530	2,042	0.31	595,023	10,587	102,271	5,685	0.35	0.05	0.10	0.02
0.95	3,491	1,751	0.33	598,514	7,096	104,022	3,934	0.36	0.04	0.07	0.02
1.00	7,096	3,934	0.36	605,610	0	107,956	0	nan	0.00	0.00	0.00

KBFC\_5\_Fold\_alpha\_balanced\_gamma\_0\_0\_Easy\_Test



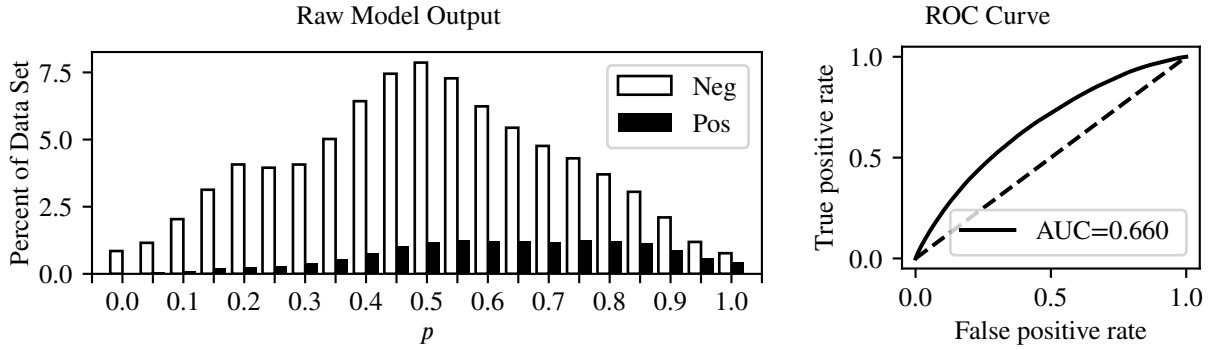
	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
p											
0.00	0	0	nan	0	605,610	0	107,956	0.15	1.00	5.61	1.00
0.05	6	0	0.00	6	605,604	0	107,956	0.15	1.00	5.61	1.00
0.10	921	11	0.01	927	604,683	11	107,945	0.15	1.00	5.60	1.00
0.15	5,562	152	0.03	6,489	599,121	163	107,793	0.15	1.00	5.55	0.99
0.20	16,339	699	0.04	22,828	582,782	862	107,094	0.16	0.99	5.40	0.97
0.25	33,010	1,935	0.06	55,838	549,772	2,797	105,159	0.16	0.97	5.09	0.92
0.30	46,388	3,164	0.06	102,226	503,384	5,961	101,995	0.17	0.94	4.66	0.85
0.35	44,779	4,222	0.09	147,005	458,605	10,183	97,773	0.18	0.91	4.25	0.78
0.40	65,386	7,295	0.10	212,391	393,219	17,478	90,478	0.19	0.84	3.64	0.68
0.45	83,274	11,544	0.12	295,665	309,945	29,022	78,934	0.20	0.73	2.87	0.54
0.50	82,857	13,545	0.14	378,522	227,088	42,567	65,389	0.22	0.61	2.10	0.41
0.55	67,651	13,728	0.17	446,173	159,437	56,295	51,661	0.24	0.48	1.48	0.30
0.60	53,985	13,162	0.20	500,158	105,452	69,457	38,499	0.27	0.36	0.98	0.20
0.65	45,343	13,766	0.23	545,501	60,109	83,223	24,733	0.29	0.23	0.56	0.12
0.70	34,288	12,641	0.27	579,789	25,821	95,864	12,092	0.32	0.11	0.24	0.05
0.75	18,499	8,061	0.30	598,288	7,322	103,925	4,031	0.36	0.04	0.07	0.02
0.80	6,157	3,278	0.35	604,445	1,165	107,203	753	0.39	0.01	0.01	0.00
0.85	1,090	708	0.39	605,535	75	107,911	45	0.38	0.00	0.00	0.00
0.90	73	45	0.38	605,608	2	107,956	0	0.00	0.00	0.00	0.00
0.95	2	0	0.00	605,610	0	107,956	0	nan	0.00	0.00	0.00
1.00	0	0	nan	605,610	0	107,956	0	nan	0.00	0.00	0.00

KBFC\_5\_Fold\_alpha\_balanced\_gamma\_0\_0\_Easy\_Test\_Transformed\_100



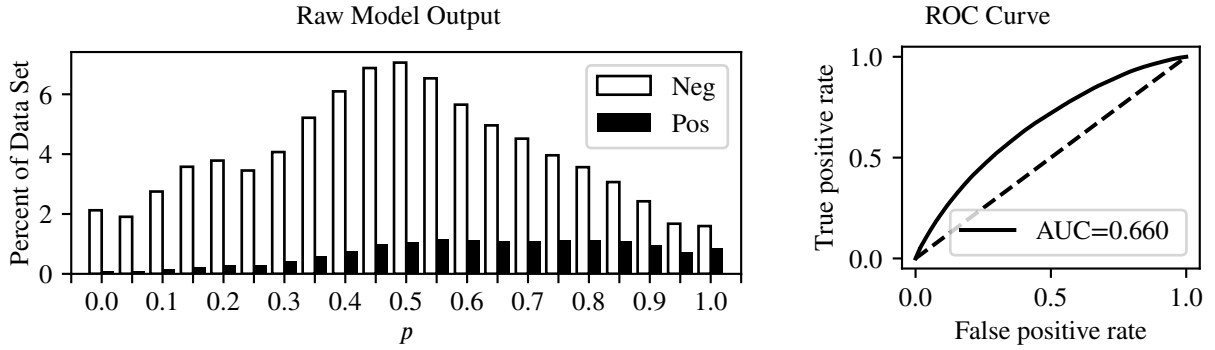
$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	1	0	0.00	1	605,609	0	107,956	0.15	1.00	5.61	1.00
0.05	166	3	0.02	167	605,443	3	107,953	0.15	1.00	5.61	1.00
0.10	2,683	60	0.02	2,850	602,760	63	107,893	0.15	1.00	5.58	1.00
0.15	7,711	256	0.03	10,561	595,049	319	107,637	0.15	1.00	5.51	0.98
0.20	17,534	788	0.04	28,095	577,515	1,107	106,849	0.16	0.99	5.35	0.96
0.25	29,814	1,818	0.06	57,909	547,701	2,925	105,031	0.16	0.97	5.07	0.91
0.30	40,529	2,747	0.06	98,438	507,172	5,672	102,284	0.17	0.95	4.70	0.85
0.35	37,670	3,310	0.08	136,108	469,502	8,982	98,974	0.17	0.92	4.35	0.80
0.40	49,066	5,267	0.10	185,174	420,436	14,249	93,707	0.18	0.87	3.89	0.72
0.45	66,603	8,412	0.11	251,777	353,833	22,661	85,295	0.19	0.79	3.28	0.62
0.50	73,302	10,853	0.13	325,079	280,531	33,514	74,442	0.21	0.69	2.60	0.50
0.55	67,734	11,869	0.15	392,813	212,797	45,383	62,573	0.23	0.58	1.97	0.39
0.60	56,097	11,499	0.17	448,910	156,700	56,882	51,074	0.25	0.47	1.45	0.29
0.65	46,691	11,334	0.20	495,601	110,009	68,216	39,740	0.27	0.37	1.02	0.21
0.70	39,913	11,634	0.23	535,514	70,096	79,850	28,106	0.29	0.26	0.65	0.14
0.75	32,605	11,377	0.26	568,119	37,491	91,227	16,729	0.31	0.15	0.35	0.08
0.80	22,568	9,107	0.29	590,687	14,923	100,334	7,622	0.34	0.07	0.14	0.03
0.85	10,763	5,175	0.32	601,450	4,160	105,509	2,447	0.37	0.02	0.04	0.01
0.90	3,419	1,974	0.37	604,869	741	107,483	473	0.39	0.00	0.01	0.00
0.95	682	432	0.39	605,551	59	107,915	41	0.41	0.00	0.00	0.00
1.00	59	41	0.41	605,610	0	107,956	0	nan	0.00	0.00	0.00

KBFC\_5\_Fold\_alpha\_balanced\_gamma\_0\_0\_Easy\_Test\_Transformed\_98



$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	6,067	154	0.02	6,067	599,543	154	107,802	0.15	1.00	5.55	0.99
0.05	8,241	330	0.04	14,308	591,302	484	107,472	0.15	1.00	5.48	0.98
0.10	14,535	664	0.04	28,843	576,767	1,148	106,808	0.16	0.99	5.34	0.96
0.15	22,345	1,349	0.06	51,188	554,422	2,497	105,459	0.16	0.98	5.14	0.92
0.20	29,056	1,857	0.06	80,244	525,366	4,354	103,602	0.16	0.96	4.87	0.88
0.25	28,203	2,091	0.07	108,447	497,163	6,445	101,511	0.17	0.94	4.61	0.84
0.30	29,047	2,664	0.08	137,494	468,116	9,109	98,847	0.17	0.92	4.34	0.79
0.35	35,828	3,792	0.10	173,322	432,288	12,901	95,055	0.18	0.88	4.00	0.74
0.40	45,878	5,448	0.11	219,200	386,410	18,349	89,607	0.19	0.83	3.58	0.67
0.45	53,165	7,280	0.12	272,365	333,245	25,629	82,327	0.20	0.76	3.09	0.58
0.50	56,125	8,340	0.13	328,490	277,120	33,969	73,987	0.21	0.69	2.57	0.49
0.55	51,942	8,965	0.15	380,432	225,178	42,934	65,022	0.22	0.60	2.09	0.41
0.60	44,500	8,730	0.16	424,932	180,678	51,664	56,292	0.24	0.52	1.67	0.33
0.65	38,821	8,672	0.18	463,753	141,857	60,336	47,620	0.25	0.44	1.31	0.27
0.70	33,987	8,471	0.20	497,740	107,870	68,807	39,149	0.27	0.36	1.00	0.21
0.75	30,688	8,847	0.22	528,428	77,182	77,654	30,302	0.28	0.28	0.71	0.15
0.80	26,427	8,722	0.25	554,855	50,755	86,376	21,580	0.30	0.20	0.47	0.10
0.85	21,795	8,188	0.27	576,650	28,960	94,564	13,392	0.32	0.12	0.27	0.06
0.90	14,996	6,175	0.29	591,646	13,964	100,739	7,217	0.34	0.07	0.13	0.03
0.95	8,481	4,075	0.32	600,127	5,483	104,814	3,142	0.36	0.03	0.05	0.01
1.00	5,483	3,142	0.36	605,610	0	107,956	0	nan	0.00	0.00	0.00

KBFC\_5\_Fold\_alpha\_balanced\_gamma\_0\_0\_Easy\_Test\_Transformed\_95



$p$	Neg	Pos	mPrec	TN	FP	FN	TP	Prec	Rec	FP/P	$\hat{p}$
0.00	15,159	519	0.03	15,159	590,451	519	107,437	0.15	1.00	5.47	0.98
0.05	13,605	626	0.04	28,764	576,846	1,145	106,811	0.16	0.99	5.34	0.96
0.10	19,628	1,172	0.06	48,392	557,218	2,317	105,639	0.16	0.98	5.16	0.93
0.15	25,531	1,623	0.06	73,923	531,687	3,940	104,016	0.16	0.96	4.93	0.89
0.20	27,006	1,929	0.07	100,929	504,681	5,869	102,087	0.17	0.95	4.67	0.85
0.25	24,639	2,067	0.08	125,568	480,042	7,936	100,020	0.17	0.93	4.45	0.81
0.30	29,041	3,003	0.09	154,609	451,001	10,939	97,017	0.18	0.90	4.18	0.77
0.35	37,221	4,071	0.10	191,830	413,780	15,010	92,946	0.18	0.86	3.83	0.71
0.40	43,510	5,447	0.11	235,340	370,270	20,457	87,499	0.19	0.81	3.43	0.64
0.45	49,072	6,936	0.12	284,412	321,198	27,393	80,563	0.20	0.75	2.98	0.56
0.50	50,369	7,619	0.13	334,781	270,829	35,012	72,944	0.21	0.68	2.51	0.48
0.55	46,616	8,122	0.15	381,397	224,213	43,134	64,822	0.22	0.60	2.08	0.41
0.60	40,340	7,879	0.16	421,737	183,873	51,013	56,943	0.24	0.53	1.70	0.34
0.65	35,403	7,768	0.18	457,140	148,470	58,781	49,175	0.25	0.46	1.38	0.28
0.70	32,235	7,786	0.19	489,375	116,235	66,567	41,389	0.26	0.38	1.08	0.22
0.75	28,270	7,938	0.22	517,645	87,965	74,505	33,451	0.28	0.31	0.81	0.17
0.80	25,437	7,875	0.24	543,082	62,528	82,380	25,576	0.29	0.24	0.58	0.12
0.85	21,881	7,665	0.26	564,963	40,647	90,045	17,911	0.31	0.17	0.38	0.08
0.90	17,302	6,800	0.28	582,265	23,345	96,845	11,111	0.32	0.10	0.22	0.05
0.95	11,952	5,034	0.30	594,217	11,393	101,879	6,077	0.35	0.06	0.11	0.02
1.00	11,393	6,077	0.35	605,610	0	107,956	0	nan	0.00	0.00	0.00

## Funding Statement

## Conflict of Interest

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

## Acknowledgements

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

## Data Availability

The CRSS data is publicly available at

<https://www.nhtsa.gov/crash-data-systems/crash-report-sampling-system>

## Declaration of Generative AI and AI-assisted technologies in the writing process

17.

## CRedit authorship contribution statement

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

## References

- Herbert, G., 2019. Crash Report Sampling System: Imputation. Technical Report DOT HS 812 795. National Highway Traffic Safety Administration.
- 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.
- Ma, Y., Xie, Z., Chen, S., Qiao, F., Li, Z., 2023. Real-time detection of abnormal driving behavior based on long short-term memory network and regression residuals. Transportation Research Part C: Emerging Technologies 146, 103983. URL: <https://www.sciencedirect.com/science/article/pii/S0968090X22003965>, doi:<https://doi.org/10.1016/j.trc.2022.103983>.
- Raghunathan, T., Solenberger, P., Berglund, P., van Hoewyk, J., . Iware: Imputation and variation estimation software. URL: <https://www.src.isr.umich.edu/software/iware/>.