Predicting Coupon Acceptance Using Machine Learning Algorithms

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Abstract

In this project, several machine learning algorithms were applied to a binary classification task to maximize prediction accuracy. The data set was generated by a survey on Amazon Mechanical Turk, which offered "Turkers" with high ratings targeted "20% off" coupons to local businesses. The goal was to predict whether a given coupon had been accepted based on information about the user, context, and coupon. To this end, the data set was explored and cleaned. Following feature engineering, four machine learning algorithms, Support Vector Machines (SVM), Random Forest, AdaBoost, and XGBoost were implemented. For each algorithm, hyperparameters were tuned using cross-validation, and model reliance was calculated for models with optimal hyperparameters, providing a measure of variable importance. Weighted averages of predicted probabilities between tuned models were also considered to increase predictive accuracy. An ensemble formed by a simple average of XGBoost and SVM predictions achieved the best observed test accuracy of 77.92%.

1 - Introduction

This portfolio project utilized an in-vehicle coupon recommendation data set, which was generated via a survey on Amazon Mechanical Turk [1]. In this survey, Turkers with high ratings (95% or above) were offered targeted "20% off" coupons to local businesses. Respondents who said they would drive to the coupon location "right away" or "later before the coupon expires" were marked as "Decision = 1", while users who answered "no, I do not want the coupon" were marked as "Decision = 0." A number of user attributes (e.g., gender, age), contextual attributes (e.g., driving destination, time of day), and coupon attributes (i.e., time to expiry) were included in the data set, which contained 10,184 training observations and 2,500 test observations (see Appendix for data dictionary). The challenge, then, was to try to predict (i.e., classify) whether a given coupon had been accepted based on the provided information.

2 - Exploratory Analysis

Variable types: While the data set contained variables with a mix of default variable types (i.e., categorical, numeric), it was ultimately decided that all variables should be categorical. None of the seemingly numeric features were continuous, nor did gaps between the discrete values of the variables have intuitive numerical meaning.

Missing data: Though no single variable had more than 182 missing values in the training data set, there were 495 total observations with at least one missing value, which constituted almost 5% of the training data set. Rather than remove that much data, the missing values were simply replaced with the string "NA," which created an additional rating category, given the categorical nature of the variables.

Feature engineering: The `id` variable was removed because it was simply a unique identifier for the survey observation. Second, a `Coupon_category_rating`, equal to the value of `Bar`, `Coffeehouse`, `Carryaway`, `Restaurantlessthan20`, or `Restaurant20to50` corresponding to the type of `Coupon`, was created. For example, if a `Coupon` was issued for a bar, and the respondent had a value of 3 for the `Bar` variable, then `Coupon_category_rating` would be set to 3.

Exploratory data analysis focused on (1) counts and (2) observed incidence of Decision = 1 for each category within each variable (see Figure 1 for an example visualization). Of particular interest, the response variable was fairly balanced with ~57% of respondents accepting the coupon. All categories within each variable had at least 34 responses with the vast majority having over 100 responses.

3 - Methods

Four different algorithms were considered for this prediction task: Support Vector Machines (SVM), Random Forest, AdaBoost, and XGBoost. This section is organized by algorithm and covers both a brief description of the algorithm and a description of the training procedure.

Support Vector Machines (SVM) [2, 3]

In the fully separable case, SVMs aim to create a decision boundary that maximizes the distance from the decision boundary to the nearest training observation. In most real-life applications, however, data are not perfectly separable (without tremendous overfitting), and the SVM framework can be adapted to include a slack term. This slack term allows the minimum margin to be less than 1 but adds a penalty term to the optimization problem in the form of the hinge loss.

In this project, a Gaussian kernel is used to fit the data, which constructs decision boundaries by centering a Gaussian distribution on each data point. This kernel provides a great deal of flexibility but also risks overfitting training data if not tuned properly. In particular, the σ^2 parameter in the kernel defines the shape of the Gaussian distribution centered on each data point, where a value of σ^2 that is too small will overfit the data, and a value of σ^2 that is too large will create decision boundaries that do a poor job of classifying.

A simple 10-fold cross-validation scheme was used to tune the value of σ^2: The training data was divided equally into 10 segments. Iteratively, one segment was held out as a test set, and the SVM was trained on the remaining 9 segments. The test set accuracy was then averaged across all 10 test segments. This process was repeated (using the same 10 folds) for 8 different values of σ^2, ranging from 1 to 128.

Random Forest [2, 4]

Random Forests were born out of the idea that averaging the votes of diverse decision trees leads to strong predictive power. To fit each tree within a Random Forest, a bootstrap sample (equivalent in size to the original data set) is drawn. In creating a tree, only m out of p of the possible predictors is considered at each split, and the tree is grown until a minimum number of observations is present at each leaf. In the package used for this project, CART trees are used as the base estimator, meaning that Gini index is used as the splitting criteria. Additionally, m is defined as $\sqrt{p}$, and the minimum number of observations in a leaf is 1.

Predictions are made based on majority vote across all of the trees grown in the Random Forest, which reduces the variance / level of overfitting that would be achieved from a single, un-pruned tree. The number of trees is the main hyperparameter that must be tuned, and the same 10-fold cross-validation strategy described in the SVM section was used to evaluate 6 values, ranging from 10 to 500.

AdaBoost [2, 5]

In general, boosting seeks to address the challenge of turning a “weak learning algorithm” into a “strong learning algorithm.” Freund and Schapire developed AdaBoost, which can be described in two different ways.

Re-weighting data: At each iteration, the algorithm assigns higher weights to data points that have been classified incorrectly so that these misclassified observations will be emphasized during the next iteration. Additionally, the contribution of each weak classifier to the final prediction is based on its training prediction accuracy.

Coordinate descent: At each iteration, the algorithm chooses the direction (i.e., the weak classifier) that will produce the steepest decrease in the exponential loss. Then, the step-size (i.e., contribution to the final model) is determined based on the training accuracy of the chosen weak classifier.

Typically, decision trees are used as the weak classifiers in AdaBoost, and for this project, CART decision trees were used. Both the number of trees (like Random Forest) and the depth of each tree (unlike Random Forest) are hyperparameters that need to be tuned for the AdaBoost algorithm. The same 10-fold cross-validation strategy described in the SVM section was used to evaluate a grid of 6 different values for number of trees (from 10 to 500) and 8 different values for maximum depth (1-8).

XGBoost [2, 6]

XGBoost is another boosting algorithm that aims to turn a weak learning algorithm into a strong learning algorithm. As with AdaBoost, predictions are based on a weighted sum of opinions from all of the weak classifiers. To highlight a few of the main differences between XGBoost and AdaBoost:

- The weak classifier in iteration t of XGBoost is built off of the residuals of the weak classifier in iteration t - 1
- XGBoost seeks to minimize the logistic loss, while AdaBoost seeks to minimize the exponential loss
- In XGBoost, the learning rate determines how much each new weak classifier contributes to the final model and is typically the same for all weak classifiers

As with AdaBoost, decision trees are typically used as base estimators for XGBoost, and for this project, CART decision trees were used. Accordingly, number of trees and maximum depth of each tree were hyperparameters that needed to be tuned. Additionally, the learning rate can be highly influential in model performance and needed to be tuned.

The need to tune three different hyperparameters, each with a wide range of plausible values, motivated the use of a different type of cross-validation, randomized search CV. In this method, a distribution of values is provided for each hyperparameter of interest. At each iteration in the cross-validation procedure, values are drawn from these hyperparameter distributions at random, and k-fold cross-validation is performed (5-fold was chosen instead of 10-fold due to computational time). Then, at the end of the procedure, the hyperparameters of the best performing model (on average across the k folds) are returned.

4 - Discussion and Results

Table 1 provides a summary of chosen hyperparameters, training error, and test error for the four algorithms discussed in the previous section. Of note, the SVM model achieved the highest training (77.13%) and test (76.68) accuracy, followed closely by XGBoost (76.53%, 76.28%). All algorithms produced models that generated accuracy values within a range of 2.5 percentage points on both training (74.81% - 77.13%) and test (74.24% - 76.68%) sets. See Figures 2-5 and Tables 2-3 for more detailed results from hyperparameter tuning.

To further improve predictive accuracy, ensembles of multiple models were considered. The best models for each algorithm were used to predict probabilities of test observations belonging to each class (as opposed to simply predicting a 0 or 1 label). It was observed that nearly all of the predicted probabilities for AdaBoost were within 0.01 of 0.5 (see Figures 6-7). As a result, predicted probabilities for all models were calibrated using the `CalibratedClassifierCV` function within scikit-learn [2]. While numerous combinations of algorithms were considered (see Table 4), a simple average in calibrated predicted probabilities between the SVM and XGBoost models produced the best observed test accuracy of 77.92%.

In addition to computing model accuracy, it was of interest to determine which variables were most "important" for the best-performing models from each algorithm. Given that one-hot encoded data sets were used to train all of the models, a custom model reliance function was written to group all relevant columns together (e.g., the "Bar" feature had become 5 one-hot encoded variables). These groups of columns were then permuted in the test set, and test errors were calculated. Out of convenience (i.e., readily available scikit-learn functions), hinge loss was used for the SVM model reliance calculation, while logistic loss was used for all other algorithms. The five most important features for each algorithm are shown in Table 5, and `Coupon_category_rating` and `Coupon` appear in the top three for all algorithms.

5 - Citations and Acknowledgements

This portfolio project is based on an end-of-semester Kaggle competition in Professor Cynthia Rudin's STA 671 course (Theory and Algorithms for Machine Learning, Fall 2021).

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2. Pedregosa, F. et al., 2011. Scikit-learn: Machine learning in Python. Journal of machine learning research, 12(Oct), pp.2825–2830.
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5. Freund, Y, Schapire, R. "A Decision-Theoretic Generalization of On-Line Learning and an Application to Boosting." Journal of Computer and System Sciences. 1997. 119-139
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6 - Appendix

Data Dictionary [1]

The attributes of this data set include:

1. User attributes

- `Gender`: male, female
- `Age`: below 21, 21 to 25, 26 to 30, etc.
- `Maritalstatus`: single, married partner, unmarried partner, or widowed
- `Children`: 0, 1, or more than 1
- `Education`: high school, bachelors degree, associates degree, or graduate degree
- `Occupation`: architecture & engineering, business & financial, etc.
- `Income`: less than $12500, $12500 - $24999, $25000 - $37499, etc.
- `Bar`: Number of times that he/she goes to a bar - 0, less than 1, 1 to 3, 4 to 8 or greater than 8
- `Carryaway`: Number of times that he/she buys takeaway food - 0, less than 1, 1 to 3, 4 to 8 or greater than 8
- `Coffeehouse`: Number of times that he/she goes to a coffee house - 0, less than 1, 1 to 3, 4 to 8 or greater than 8
- `Restaurantlessthan20`: Number of times that he/she eats at a restaurant with average expense less than $20 per person - 0, less than 1, 1 to 3, 4 to 8 or greater than 8
- `Restaurant20to50`: Number of times that he/she eats at a restaurant with average expense $20-50 per person - 0, less than 1, 1 to 3, 4 to 8 or greater than 8

2. Contextual attributes

- `Driving_to`: home, work, or no urgent destination
- `Direction_same`: we provide a map to show the geographical location of the user, destination, and the venue, and we mark the distance between each two places with time of driving. The user can see whether the venue is in the same direction as the destination.
- `Weather`: sunny, rainy, or snowy
- `Temperature`: 30F, 55F, or 80F
- `Time`: 10AM, 2PM, or 6PM

- `Passenger`: alone, partner, kid(s), or friend(s)

3. Coupon attributes

- `Coupon_validity`: 2 hours or one day
- `Coupon`: Coupon category (e.g., bar, coffeehouse)

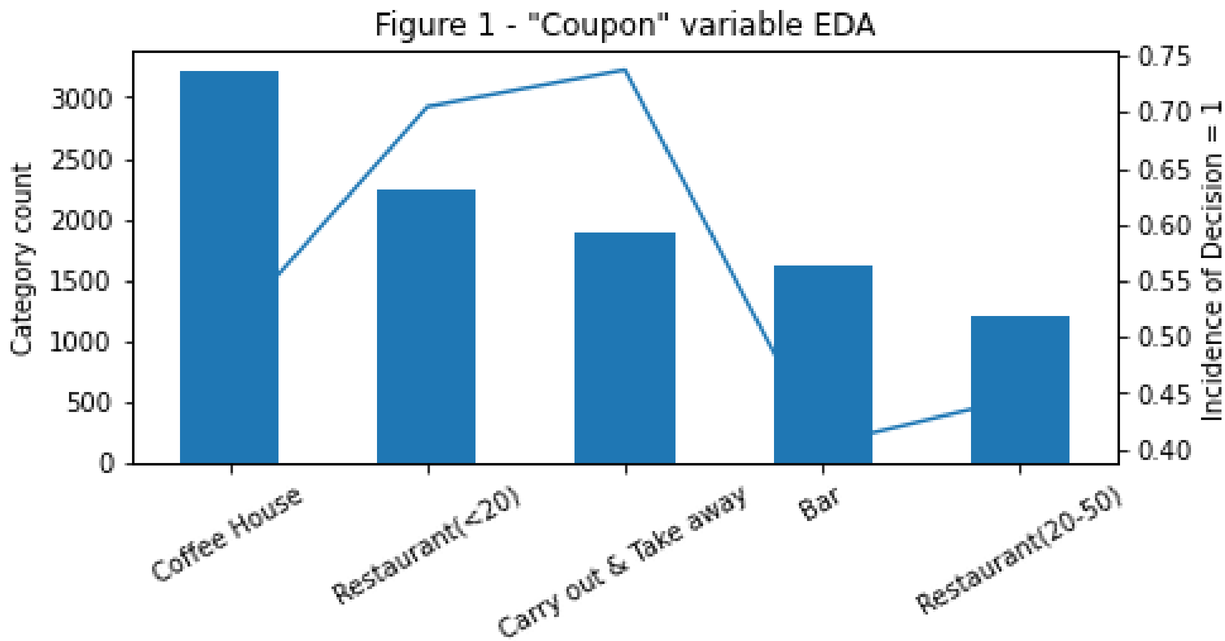
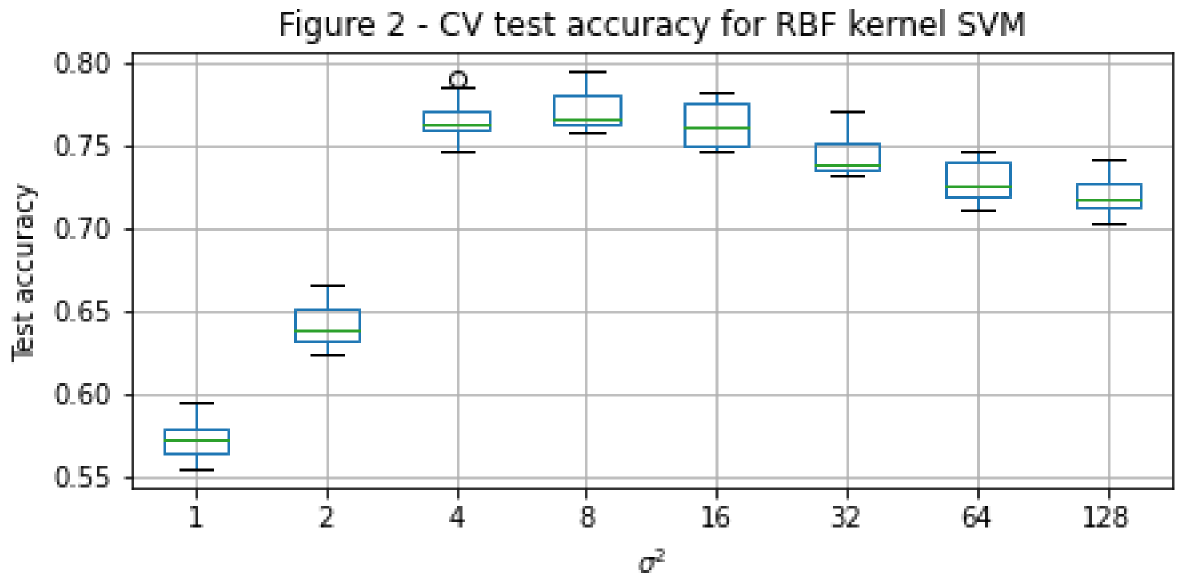


Table 1 - Summary of results

Algorithm	Hyperparameters	Train_error	Test_error
SVM	Gamma = 1/8	77.13%	76.68%
XGBoost	Num_trees = 189, max_depth = 6, learning_rate = 0.2388	76.53%	76.28%
Random Forest	Num_trees = 175	76.35%	75.56%
AdaBoost	Num_trees = 250, max_depth = 2	74.81%	74.24%



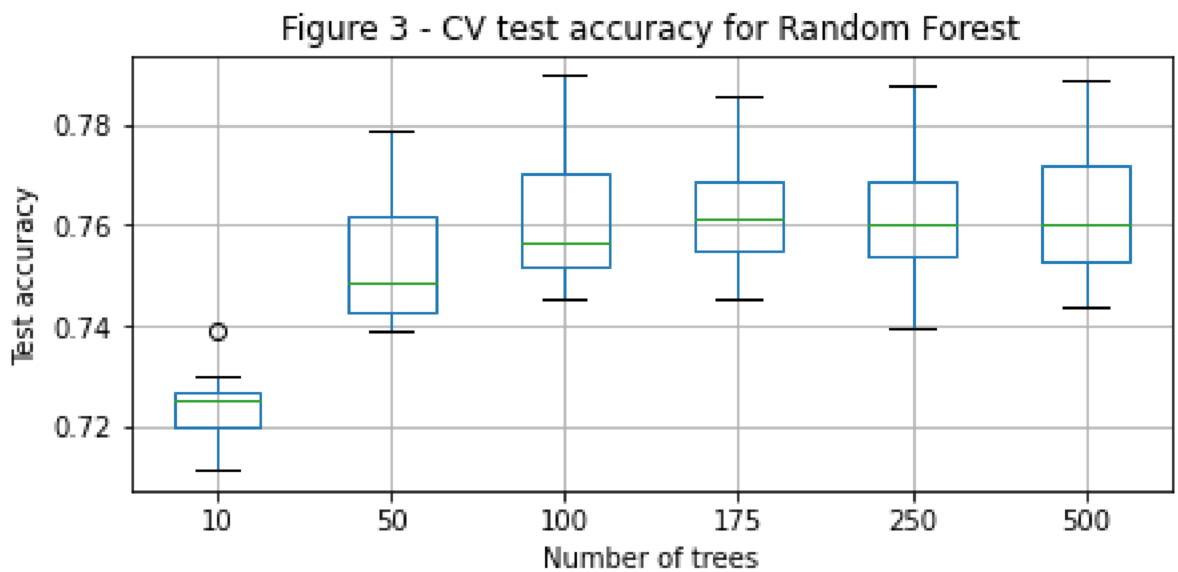
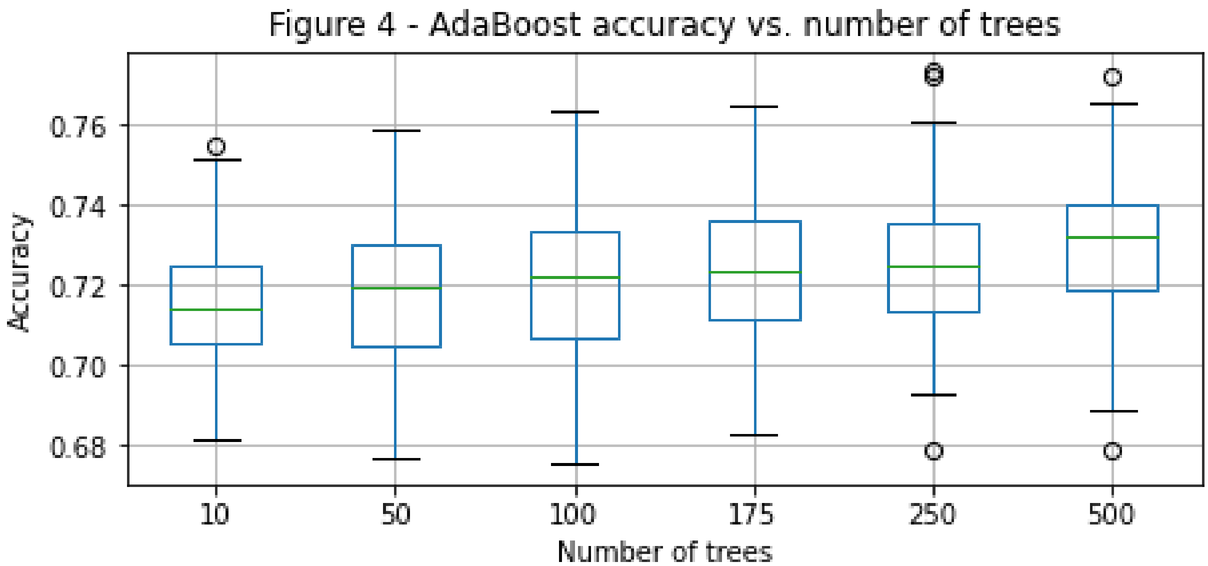


Table 2 - Top AdaBoost models

	n_trees	depth	accuracy
0	250	2	0.748133
1	100	3	0.745972
2	500	2	0.743323
3	175	2	0.742244
4	175	3	0.740571



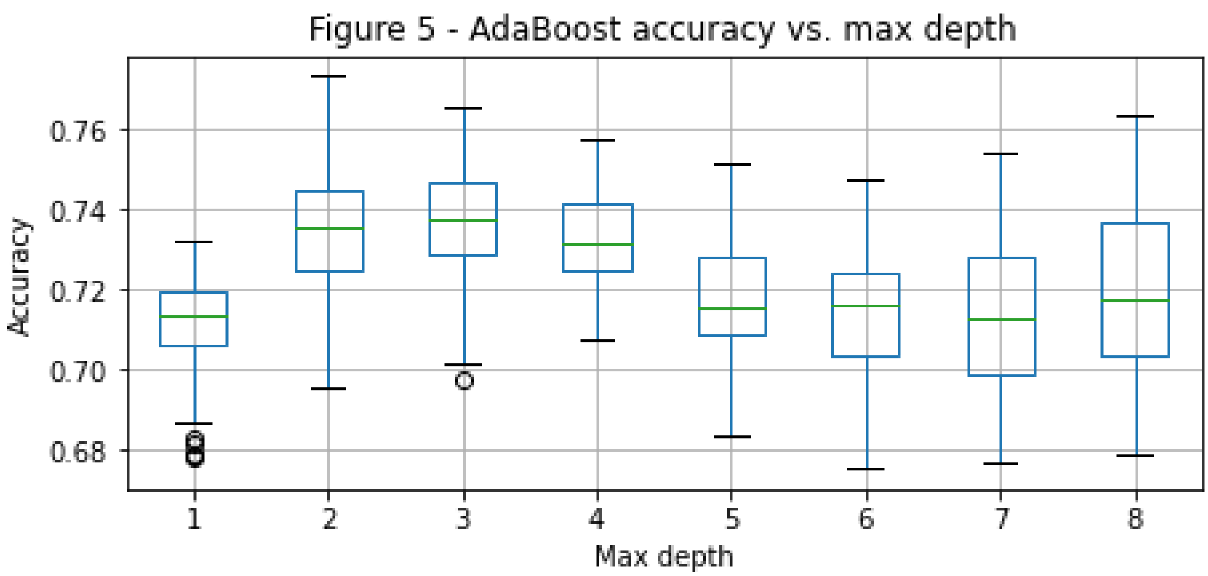


Table 3 - Top XGBoost models

param_learning_rate	param_max_depth	param_n_estimators	mean_test_score
0.238814	6	189	0.765711
0.266982	7	188	0.764827
0.115118	7	216	0.764239
0.274391	5	284	0.763846
0.200182	7	298	0.763747

Figure 6 - Predicted probabilities after calibration

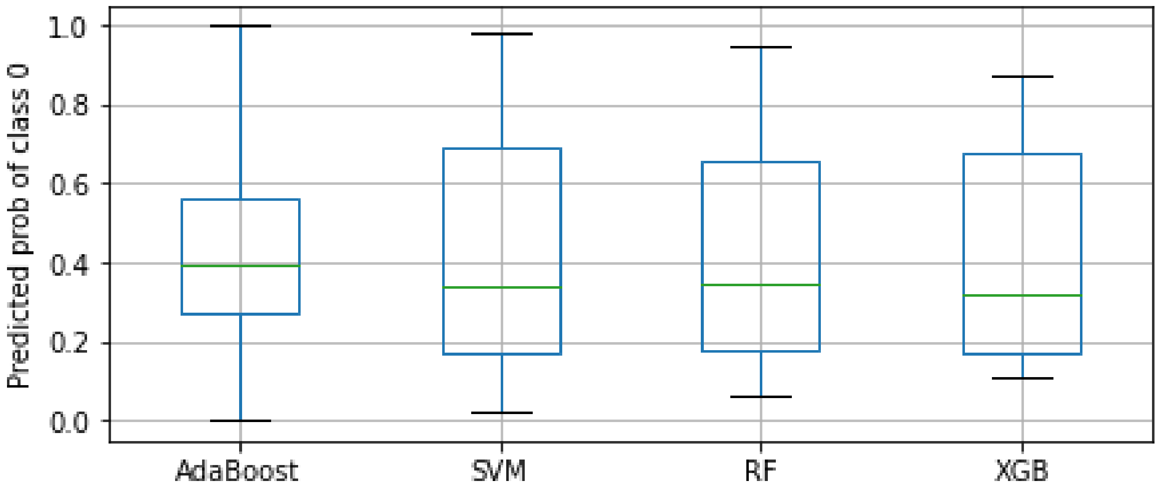


Figure 7 - AdaBoost calibration

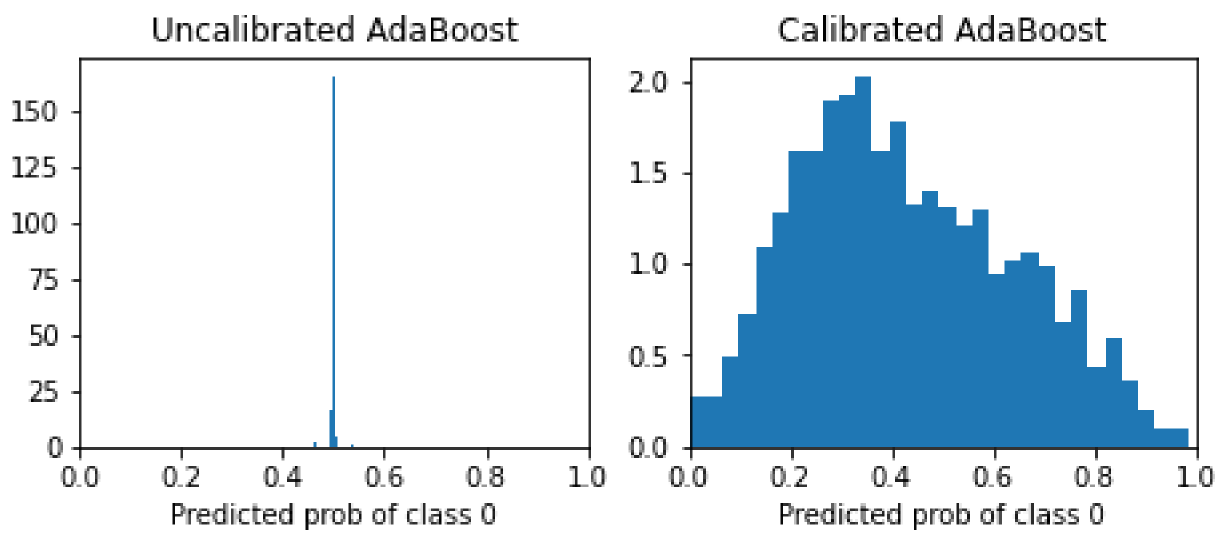


Table 4 - Ensemble model coefficients vs. validation set CV accuracy

	AdaBoost	SVM	RF	XGB	Avg
0	0.156923	0.453096	0.308165	0.081815	0.785958
1	0.165900	0.433677	0.292717	0.107706	0.784971
2	0.217445	0.270480	0.322461	0.189614	0.784971
3	0.147930	0.478480	0.275075	0.098515	0.784971
4	0.150347	0.408540	0.304664	0.136449	0.784483

Table 5 - Top 5 features per model, based on model reliance

Rank	SVM	Random_Forest	AdaBoost	XGBoost
1	Coupon_category_rating	Coupon_category_rating	Coupon_category_rating	Coupon_category_rating
2	Coupon_validity	Coupon	Coupon	Coupon
3	Coupon	Coupon_validity	Occupation	Coupon_validity
4	Income	Occupation	Income	Occupation
5	Occupation	Restaurantlessthan20	Driving_to	Maritalstatus