INDIVIDUAL ASSIGNMENT

TECHNOLOGY PARK MALAYSIA

CT046-3-M-AML

APPLIED MACHINE LEARNING

APDMF2112DSBA(DE)(PR)

APRIL 2022

TITLE: E-COMMERCE PACKAGE DELIVERY TIME PREDICTION USING MACHINE LEARNING

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ABSTRACT

Proportional to the rapid growth of e-commerce industry is the package delivery services. By providing accurate package delivery time, operation efficiency enhances and customer retention rate increases. The adoption of machine learning methods to predict the package delivery time has garnered popularity due to the wide applicability of machine learning and the accuracies of the predictions. Common issue with machine learning in this domain is feature selection as variety of data can be collected from each leg of the supply chain. This study aimed to develop prediction models using machine learning algorithms to predict the package delivery time. An e-commerce shipping dataset from Kaggle consisting of customer and package shipment information is utilized for this prediction task. The prediction task is a binary classifier to predict whether the package is delivered on time or not on time. The prediction models are developed using Logistic Regression, XGBoost, AdaBoost, and Random Forest algorithms. Furthermore, each algorithm is used to build two models namely the basic model with hyperparameters as default setting values and an optimized model with hyperparameter optimization using grid search over a wide range of hyperparameter combinations. Among the four developed models, the optimized AdaBoost model obtained the best performance with an accuracy of 69.82% and outperformed the literature that uses the same dataset.

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LIST OF ABBREVIATIONS

AdaBoost..............Adaptive Boosting
ANN.....................Artificial Neural Network
CatBoost...............Categories Boosting
CV........................Cross Validation
XGBoost ....Extreme Gradient Boosting
GRU ....Gated Recurrent Unit
KNN.....................K-Nearest Neighbor
LightGBM............Light Gradient Boosting Machine
LSTM...................Long Short-Term Memory
MAE.....................Mean Absolute Error
RF.........................Random Forest
ROC ....Receiver Operating Characteristic
RMSE...................Root Mean Square Error
SVM.....................Support Vector Machine
SVR......................Support Vector Regression

SECTION 1

INTRODUCTION

1.1 INTRODUCTION

The e-commerce has seen an exponential growth in recent years due to the movement restriction order caused by the COVID-19 pandemic which pushed people to commerce online more than ever. In which the increased in e-commerce activities led to the increased demand of package delivery services. The package delivery time plays an important role in maintaining supply chain efficiency and customer retention (Khiari & Olaverri-Monreal, 2020). Therefore, accurate delivery time allows the optimization of delivery routes and provides information to customers to allow time coordination to ensure high successful delivery rate. In addition, providing accurate delivery time increases the customer experience and confidence towards the delivery company and seller (Hildebrandt & Ulmer, 2021). Since e-commerce lacked the physical component of being able to examine the product upfront, customers associate brands and products with the quality of service the sellers provide which one of the indicator is on time product delivery (Magiya, 2020).

The prediction of package delivery time is a very challenging task due to the multitude of uncertainties which involve in every leg of the supply chain. As the world is getting more interconnected, products are being sold and bought from different parts of the world. In which this would involve the use of different transportation mode to ship packages, which each of them carries their own unique challenges. The uncertainties can include traffic conditions, weather conditions, etc. In addition, peak seasons due to holidays or weekends may contribute to increased uncertainties as delivery orders surge. Sundaram and Tallamraju (2021) mentioned that providing information to customers about the estimated delivery date is a double-edged sword as the actual delivery can be earlier or later even by just one day from the estimated date would lead to a bad customer experience and would likely result in a customer churn.

Due to the multitude of uncertainties involved, the utilization of machine learning and deep learning approaches are adopted in predicting the package delivery time as claimed by their capabilities of being able to solve complex and non-linear problems. In particular, the utilization of boosting-based algorithms has garnered popularity in predicting the delivery time due to the fast computation and high accuracy (Magiya, 2020; Sundaram & Tallamraju, 2021). Examples of widely used boosting-based algorithms include Light Gradient Boosting Machine (LightGBM), XGBoost, Adaptive Boosting (AdaBoost), etc. Which in the industry, accurate delivery time information can provide benefits of optimizing operation flow and resource planning and management. However, to develop an accurate delivery time prediction model, it requires variety of data which covers the trip information, operational information, and customer information (Wu & Wu, 2019). Therefore, such volume and variety of data requires high computational power and time which delays the information segregation. Other types of algorithms are also used in delivery time prediction which include Artificial Neural Networks (ANN), Long-Short Term Memory (LSTM), Random Forest (RF), Support Vector Regression (SVR), Naïve Bayes, Logistic Regression, etc.

The common issue with producing an accurate delivery time prediction model is the feature selection phase (Servos *et al.*, 2019). Voluminous data is generated from each phase of the package delivery which the package traverse through multiple transition hubs before finally arriving to the last-mile hub for the final delivery. This would include multiple mode of transportation for the package such as using ships, planes, and road vehicles, where each of them tracks a different set of data and information. Therefore, large number of features are generated from a single trip of package delivery. Feature selection is utmost important to identify significant features that provide the most impact to the development of the model while eliminating the least significant features to optimize the model by reducing complexity and reducing the processing time.

This study investigates an e-commerce dataset consisting of customer and shipment data extracted from Kaggle to predict the last-mile package delivery time. The delivery time prediction is a classification problem with a binary output of either package has been delivered on time or not on time. The prediction algorithms utilized in this study includes Logistic Regression, XGBoost, AdaBoost, and Random Forest (RF).

1.2 RESEARCH QUESTION

For the purpose of this project, the following questions will be addressed:

1. What are the machine learning algorithms suitable for predicting the shipping product delivery time?
2. How are the model performance to be improved?
3. How are the prediction models to be evaluated?

1.3 AIM & OBJECTIVES

1.3.1 Aim

The aim of this study is to develop prediction models that predict the delivery time of shipping products as a classification problem whether products are delivered on time or not on time by using machine learning algorithms.

1.3.2 Objectives

The objectives of the study are as followed:

1. To identify suitable machine learning algorithms for prediction of shipping product delivery time.
2. To develop shipping product delivery time prediction models and apply hyperparameter optimization techniques to achieve better accuracy.
3. To evaluate performance of the prediction models against existing related works.

SECTION 2

LITERATURE REVIEW

2.1 LITERATURE REVIEW

A literature review on ten existing works related to the logistic domain of predicting the package delivery time is performed and tabulated in Table 2.1. Following the table, will be a discussion on the findings based on the literature review.

Table 2.1: Literature review matrix

Reference	**Dataset & Size (Row x Col)**	**Methodology**	**Result**		**Conclusion**	**Recommendation**	**Comment**
(Sundaram & Tallamraju, 2021)	Trip information data (1000000 x 8)	- Predicts shipping time of fashion products. - Feature selection performed after one-hot encoding on categorical variables. - Hyperparameter optimization to solve overfitting issue. - Algorithms: LightGBM, Random Forest, XGBoost, LSTM - Evaluation: Accuracy	LightGBM	Accuracy: 68.10%	LightGBM gave best result.	N/A	- No mention of what feature is selected. - No mention of normalizing or scaling of features.
			XGBoost	Accuracy: 58.13%			
			LSTM	Accuracy: 57.25%			
			RF	Accuracy: 55.45%			
(Ahmed *et al.*, 2021)		- Predicts parcel delivery time.	XGBoost	MAE: 14.57 minutes	XGBoost and LightGBM	Neural network of different	- Neural network did

	Trip information data (211392 x 10)	- Data merge from three datasets. - Preprocessing applied to remove duplicates and outliers. - Imputation for missing values by interpolation. - Data formatting applied on the different dataset. - Performed feature selection by SHAP. - Algorithms: XGBoost, LightGBM, LSTM, biLSTM, GRU, SVR - Evaluation: RMSE, MAE		RMSE: 26.51 minutes	provides the best performance.	architecture and hybrid models with more complex architecture can be explored.	not outperform boosting-based algorithms. - No mention of normalizing and scaling of features.
			BiLSTM	MAE: 16.30 minutes			
				RMSE: 29.96 minutes			
			GRU	MAE: 16.56 minutes			
				RMSE: 29.97 minutes			
			LightGBM	MAE: 14.40 minutes			
				RMSE: 26.54 minutes			
			LSTM	MAE: 16.60 minutes			
				RMSE: 29.97 minutes			
			SVR	MAE: 25.77 minutes			
				RMSE: 49.48 minutes			
(Ogura *et al.*, 2021)	Vessel trip information data (414x 12)	- Studies effect of weather on vessels arrival time prediction. - Dataset was small thus chose the use of Naïve Bayes. - Algorithm: Naïve Bayes - Evaluation: Accuracy	Naïve Bayes	Accuracy: 90%	Only one model is utilized, but the weather condition plays a significant role in	Data such as congestion status en route and at destination port can be considered to improve prediction accuracy.	Naïve bayes can have better accuracy than other methods such as SVM when dataset is small.

					prediction accuracy.		
(Chandra, 2021)	E-commerce dataset (10999,12)	- Predicts parcel delivery time. - Performed feature scaling using StandardScaler. - Algorithms: Random Forest, KNN - Evaluation: Accuracy	RF	Accuracy: 65.27%	Random Forest performed better than KNN.	N/A	- No mention of feature selection.
			KNN	Accuracy: 63%			
(Bagga, 2021)	E-commerce dataset (10999,12)	- Predicts parcel delivery time. - Direct implementation of raw data to algorithms. - Algorithms: Logistic Regression, KNN - Evaluation: Accuracy	Logistic Regression	Accuracy: 65%	Logistic regression and KNN obtained same result.	N/A	- No mention of normalizing and scaling of features.
			KNN	Accuracy: 65%			
(Kumar, 2021)	E-commerce dataset (10999,12)	- Predicts parcel delivery time. - Performed feature selection by chi square test, eliminating least significant features. - Performed feature scaling using MinMaxScaler. - Performed hyperparameter tuning using grid search only on RF. - Algorithms: SVM, RF, ANN - Evaluation: Accuracy	ANN	Accuracy: 67%	ANN provides better performance than SVM and RF but not significantly lot.	N/A	- No hyperparameter tuning performed on ANN model.
			SVM	Accuracy: 66%			
			RF	Accuracy: 66%			
(Khiari & Olaverri-	Trip information	- Predicts delivery time in postal services.	Gradient boosting	MAE: 61.67 minutes	- Boosting-based	To implement weather data and	- No mention of

Monreal, 2020)	data (193684 x 7)	- Performed feature engineering from raw dataset. - Algorithms: Gradient boosting, Adaboost, Extreme gradient boosting, Light gradient boosting, Histogram gradient boosting, Catboost - Evaluation: MAE, RMSE		RMSE: 238.61 minutes	algorithms has great potential in predicting travel time. - LightGBM, Catboost, and Histogram boosting yielded a low computationa l time without compromisin g accuracy.	intermediate GPS data to improve delivery time prediction accuracy.	normalizing or scaling of features. - Evaluated the computational time of the prediction models.
			AdaBoost	MAE: 133.21 minutes RMSE: 223.13 minutes			
			Histogram gradient boosting	MAE: 48.08 minutes RMSE: 247.04 minutes			
			XGBoost	MAE: 34.41 minutes RMSE: 402.81 minutes			
			CatBoost	MAE: 67.85 minutes RMSE: 162.17 minutes			
			LightGBM	MAE: 48.10 minutes RMSE: 246.77 minutes			
(Magiya, 2020)	Trip information data (28269 x 39)	- Predicts parcel delivery time by motorcycle. - Performed feature selection.	XGBoost	Accuracy: 42.21%	Feature selection is important for model to	To study how different delivery vehicle types would affect delivery time.	- No mention of normalizing and scaling of features.

		- Performed cross validation and hold out validation. - Algorithm: XGBoost - Evaluation: Accuracy			perform better.		
(Wu & Wu, 2019)	Trip information data (350000 x 10)	- Predicts parcel delivery time. - Performed feature normalization using padding method. - Algorithm: Stacked LSTM - Evaluation: RMSE, MAPE	LSTM	RMSE: 63.58 minutes	- LSTM significantly outperforms the benchmarks on real related works.	Using data about sequence of route might improve prediction accuracy.	Combining two models output by a fully connected neural network for prediction.
(Servos *et al.*, 2019)	Trip information data (101136 x 36)	- Predicts freight delivery time. - Performed data cleansing to remove outliers and denoise. - Feature engineering and selection of significant features. - Used grid search and cross validation for parameter tuning. - Algorithms: Randomized Trees, AdaBoost, SVR - Evaluation: RMSE, MAE	Randomized Trees	MAE: 108.39 minutes	Support vector regression performed best.	To be evaluated on a larger transport fleet and different transport mode.	- No mention of normalizing and scaling of features.
				RMSE: 119.94 minutes			
			AdaBoost	MAE: 103.67 minutes			
				RMSE: 113.83 minutes			
			SVR	MAE: 31 minutes			
				RMSE: 38.88 minutes			

2.2 DISCUSSION

The logistic chain is vast and involve multiple mode of shipment, typically using ships, planes, and road vehicles. Generally, trip information data for package delivery using ships and road vehicles are frequently used in predicting the package delivery time instead of trip information data of planes. This is due to the highly uncertain events associated with this type of shipping mode such as traffic conditions, weather conditions, travel path restrictions, etc. While for deliveries using planes, less uncertainties are present due to the highly regulated and planning involved in every shipment and does not conform to the traffic and weather conditions like other mode of transport.

The most frequently used prediction algorithm is the boosting-based algorithm such as AdaBoost, XGBoost, etc. The boosting-based algorithms have garnered popularity due to the high computational speed and highly accurate result. This is due to the requirement of real time output needed for the companies to perform decision making and planning. However, in the case of Servos *et al.* (2019), it was found that SVR outperforms AdaBoost. Following that, the second frequently used algorithms are neural networks. This is due to the multidimensional data collected from each leg of the supply chain, which neural networks are claimed to perform well on such large and complex dataset. The use of neural network algorithm can be seen in the works of Kumar (2021) which performed better as compared to SVM and RF.

Missing data are typical, as data is collected from different vehicles using sensors which might malfunction due to certain reasons. However, only Ahmed *et al.* (2021) has performed missing data imputation by using interpolation method while others did not mention on missing data and how to deal with missing data. Generally, data is abundant when it is obtained from a logistic company as current technologies allowed easy implementation and tracking of vehicle movements. Therefore, authors may opt to drop the missing data instead of imputing the missing data.

Furthermore, it was observed that feature scaling and feature selection is performed on majority of the works (Chandra, 2021; Kumar, 2021; Magiya, 2020; Servos *et al.*, 2019; Wu & Wu, 2019). Feature scaling is performed due to the data consisting of various information typically in different value ranges such as trip distance, package weight, number of stops, etc. By having features in the same scale, this would improve model performance especially distance-based algorithms such as KNN. In addition, feature selection is performed to reduce model complexity as not all features provide significant impact to the model performance.

For the evaluation metric, two major groups of metrics are observed depending on the type of problems. For regression type problems, the metric MAE and RMSE is frequently used. This type of works predicts the exact time of delivery which involves more complex dataset containing higher feature numbers. It is not able to directly compare the performance between the authors due to the different dataset, subdomain, and transportation mode used which varies greatly dependent on the location of study. On the other hand, typical metric used for classification type problems is accuracy. Which mostly predicts whether package delivered on time or not on time. Comparing the works of Kumar (2021), Bagga (2021), and Chandra (2021) which originates from the same dataset. It is observed that ANN by Kumar (2021) provides the best model performance achieving an accuracy of 67%. However, the accuracies achieved by similar works average about 65% which the result achieved by ANN is not a significant improvement. Therefore, more work can be done by utilizing other methods of machine learning approaches to improve the prediction result.

SECTION 3

METHODS

3.1 DATASET

The dataset is an e-commerce shipment dataset which comprise of shipping trip information and delivery package information. The dataset comprises of 10999 observations and 12 variables. In addition, the **dependent variable** of this dataset is the feature "**Reached on time**" which is a binary class. The dataset will be used for predicting package delivery time as a classification problem of whether package is delivered on time or not on time. Table 3.1 tabulates the description for each variable in the dataset.

The dataset is retrieved from Kaggle which the link to the dataset is as followed: https://www.kaggle.com/datasets/prachi13/customer-analytics

Table 3.1: Dataset variables description

No.	Variable	Description	Labels
1	ID	Customer ID number	1 – 10999
2	Warehouse block	Warehouses which are divided into blocks	A, B, C, D, E
3	Mode of Shipment	Package transportation mode	Ship, Flight, and Road
4	Customer care calls	Customer enquiry calls about the shipment	2 – 7
5	Customer rating	Customer rating with 1 as lowest (Worst) and 5 as highest (Best)	1 – 5
6	Cost of the product	Product price in US Dollars.	96 – 310
7	Prior purchases	Prior purchase count by customers	2 – 10
8	Product importance	Product importance rating with ranking	low, medium, high
9	Gender	Male and female	M, F
10	Weight in gms	Package weight in grams	1001 – 7846
11	Discount offered	Discount offered on specific product	1 – 65
12	Reached on time	**Target variable** of product arrival time. Where **1** indicates not on time, while **0** indicates reached on time	1, 0

Table 3.2 tabulates the data type of each variable indicating the numeric or categorical variable type. It is further divided where numeric variable would be divided into continuous or integer type variable. In addition, categorical variable would be divided into nominal and ordinal type variable type.

Table 3.2: Dataset variables data type

Numerical		**Categorical**	
Continuous	**Integer**	**Nominal**	**Ordinal**
Cost of the product	Customer care calls	Warehouse block	Customer rating
Weight in gms	Prior purchases	Mode of shipment	Product importance
Discount offered		Gender	

3.2 MACHINE LEARNING ALGORITHMS

The machine learning algorithms used in the prediction models for this study will be introduced below. Four machine learning algorithms are identified based on similar use case from the literature review. The implementation of the prediction models will be performed in RStudio.

3.2.1 Logistic Regression

Logistic regression is a supervised machine learning algorithm used to predict the relationship between a dependent variable and independent variable. It is typically used for classification type problems to predict a binary class output. Application of logistic regression can be seen in medical sectors predicting a tumor as benign or malignant, incoming email classifying as spam or not spam, etc. The logistic regression is a very basic prediction algorithm which is not expected to outperform other algorithms used in this study. It is served as a benchmark model in this study as a comparison to other prediction algorithms that are more powerful.

3.2.2 Extreme Gradient Boosting (XGBoost)

XGboost is a type of boosting ensemble learning algorithm which aimed to correct errors made by previous models. The base classifier of XGBoost uses decision trees. The error correction process is sequential and iterative until no further improvements can be made. It is very popular due to its computational speed and model performance which is due to the feature of XGBoost where parallelization is adopted in the computational process. The computational speed is much faster as compared to its peers such as AdaBoost and RF. It is chosen to be used in this study due to the speed and performance that the algorithm provides.

3.2.3 Random Forest (RF)

Random Forest is a type of bagging ensemble learning algorithm where each base classifier is trained independently. Generally, the base classifier uses decision trees where each decision tree trains on a different subset of the training data. This provides diversity in each decision tree which typically results in better prediction performance as compared to a single model fitting the entire training dataset. The predictions made by the ensemble members are then aggregated using voting in the case of classification problem. Based on the literature review, boosting algorithms are a popular choice for package delivery time prediction thus is chosen for use in this study. In addition, related works that used the same dataset as this study have utilized random forest algorithm in prediction which can served as a comparison in performance after applying hyperparameter tuning (Bagga, 2021; Chandra, 2021; Kumar, 2021).

3.2.4 Adaptive Boosting (AdaBoost)

AdaBoost is a type of boosting ensemble learning algorithm where the base classifier training process is sequential and iterative. Generally, the base classifier uses decision trees where each decision tree trains on the entire training dataset with addon of sample weights from previous model. The underlying of boosting ensembles is to correct the previous prediction errors of fitted model. The second model attempts to fix the errors of previous model by fitting to the dataset and placing a higher weightage on data samples with high error rate that the previous model encountered. Therefore, greater attention is placed on samples with higher error. This process is iterated until the sample error rate remains constant. The final prediction is made by summing up each weight multiply by each tree of the entire iterative process. Based on the literature review, boosting algorithms are a popular choice for package delivery time prediction thus is chosen for use in this study. In addition, related works that used the same dataset as this study have not utilized AdaBoost algorithm in prediction which can set as the benchmark on performance of AdaBoost algorithm for the specific dataset (Bagga, 2021; Chandra, 2021; Kumar, 2021).

3.3 EVALUATION METRIC

Evaluation metrics are indicators that measure performance of the predictive model. Different evaluation measures exist dependent on the type of model either as classification or regression model. The evaluation metrics are performed to identify the predictive capability of the model when unseen data is introduced thus providing information on how well the model generalize. Following would list few evaluation metrics utilized in this study which predicts a binary classification problem.

3.3.1 Confusion Matrix

A confusion matrix is a representation of prediction results displayed in a matrix format. Typically, a confusion matrix is used for binary classification to describe the performance of the model. However, extension of the confusion matrix exists to cater for higher number of classes. Figure 3.1 shows a typical confusion matrix with binary class labels.

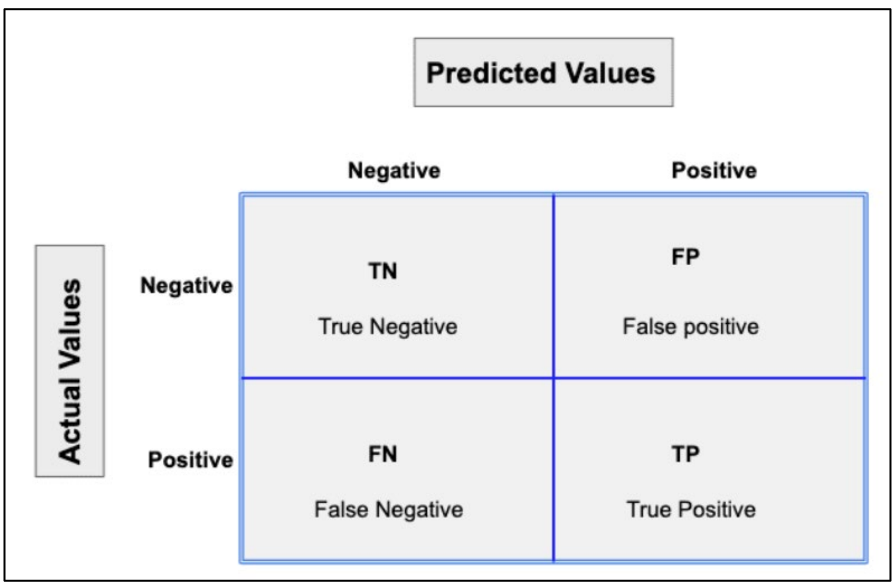

Figure 3.1: Example confusion matrix (Chauhan, 2020)

Prediction from a classification model typically is categorized into one of the quadrants of the confusion matrix. Following show the description of each quadrant of a confusion matrix:

- True Positive (TP): Predicted true, and actual is true
- True Negative (TN): Predicted false, and actual is false

- False Positive (FP): Predicted true, but actual is false
- False Negative (FN): Predicted false, but actual is true

These outcomes from the confusion matrix are further used to derive other evaluation metrics to provide more information on the model performance.

3.3.2 Accuracy

One of the metrics derived from the confusion matrix is accuracy. Accuracy is the measure of correctly predicted outcomes compared to the total outcome. A high accuracy indicates the model can generalize well to unseen data.

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

3.3.3 Specificity

Another one of the metrics derived from the confusion matrix is specificity. Specificity is the measure of how often the negative class is predicted correctly. It is the proportion of true negatives to the sum of classes that should be classified as negative. A high specificity would indicate fewer false positive results.

$$Specificity = \frac{TN}{TN + FP}$$

3.3.4 Sensitivity

Another one of the metrics derived from the confusion matrix is sensitivity. Sensitivity is the measure of how often the positive class is predicted correctly. It is the proportion of true positives to the sum of classes that should be classified as positive. A high sensitivity would indicate fewer false negative results.

$$Sensitivity = \frac{TP}{FN + FP}$$

3.3.5 Receiver Operating Characteristics (ROC)

The area under the ROC is another method to evaluate model performance. A plot of sensitivity against (1-Specificity) forms the ROC curve. The ROC can be used to visualize the trade off between true positive rate and false positive rate. Figure 3.2 shows a typical ROC curve plotted. Performance of a model is compared to the random guessing which is indicated as dashed line in the figure. Generally, the aim is to obtain a model that provides a curve that is closer to the top left corner of the chart which area under the curve is closer to one which indicates a better model. However, thresholds can be set depending on scenario which might result in other models being more favorable.

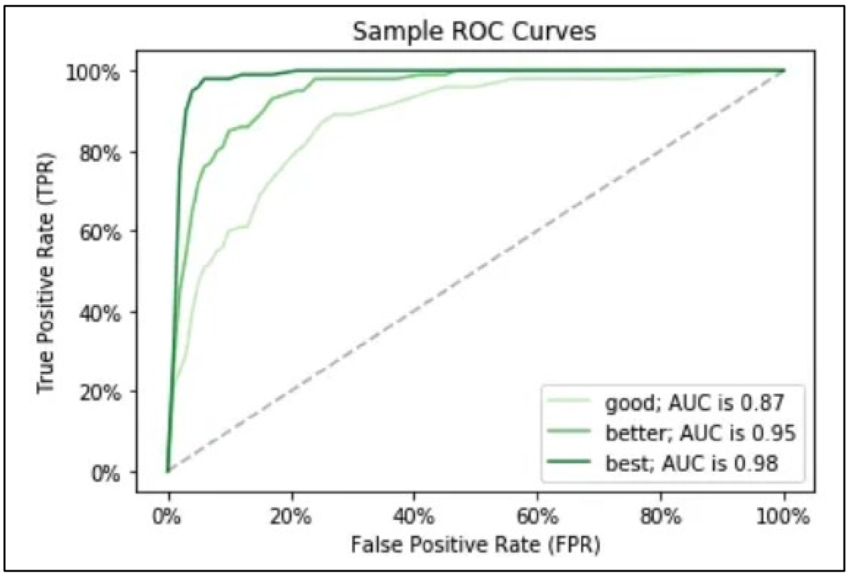

Figure 3.2: Example ROC curve (Chauhan, 2020)

3.3.6 Kappa

The Cohen's kappa is a model performance evaluation metric used for a classification model. It is typically used when the class distribution is significantly imbalanced and a multi-class output problem. It is calculated based on confusion matrix in addition considering the imbalance in class distribution. In contrast to the accuracy metric which does not consider the class distribution. The range of Cohen's kappa is from zero to one, which the value closer to one indicates a better classifier. Table 3.3 shows the interpretation of Cohen's kappa value ranges.

Table 3.3: Cohen's kappa value interpretation

Cohen's kappa value	Indicator
0.00 – 0.20	Poor agreement
0.21 – 0.40	Fair agreement
0.41 – 0.60	Moderate agreement
0.61 – 0.80	Good agreement
0.81 – 1.00	Perfect agreement

3.4 R PACKAGES

This section describe the R packages used in the study which includes for data exploratory analysis, data pre-processing, model development and validation. Table 3.4 lists the R packages used in this study along with their descriptions.

Table 3.4: R packages used

R Package Name	Description
DataExplorer	For data exploration and treatment
mice	For missing value imputation
dplyr	For data manipulation
caTools	For statistical analysis tool
caret	For model development
ROCR	For visualization of performance scoring

SECTION 4

DATASET PREPARATION

4.1 EXPLORATORY DATA ANALYSIS

The exploratory data analysis is the initial glimpse on the overall dataset to understand the characteristics of the dataset and to guide the following data pre-processing step.

4.1.1 Dataset Initial View

	ï..ID	Warehouse_block	Mode_of_Shipment	Customer_care_calls	Customer_rating	Cost_of_the_Product	Prior_purchases	Product_importance	Gender	Discount_offered	Weight_in_gms	Reached.on.Time_Y.N
1	NA	D	Flight	4	2	177	3	low	F	NA	1233	1
2	2	F	Flight	4	5	216	2	low	M	59	NA	1
3	NA	A	Flight	2	2	183	4	low	M	NA	3374	NA
4	4	B	NA	3	3	176	4	medium	M	10	1177	1
5	NA	C	Flight	2	2	NA	3	NA	F	46	2484	1

Figure 4.1: Glimpse of the first few observations of the dataset

Figure 4.1 shows the first five observation of the dataset along with all the features. Few observations are identified and listed as followed:

- Missing values are present which is annotated by 'NA' thus **missing value imputation** is required.
- Categorical variables such as warehouse block, mode of shipment, product importance, and gender require **feature encoding**.
- The value range of the features differs greatly, such as weight in grams, discount offered, and cost of product thus require **feature scaling**.
- The ID column can be **removed** as it does not provide any information and significance to the model development.

- The second instance in the feature warehouse block is showing ‘F’. Based on the metadata, warehouse block only has category ‘A’, ‘B’, ‘C’, ‘D’, and ‘E’. Further investigation is required to identify the why category ‘F’ is present in the dataset.

```
'data.frame':   10999 obs. of  12 variables:
 $ ï..ID              : int  NA 2 NA 4 NA 6 7 8 9 10 ...
 $ Warehouse_block    : chr  "D" "F" "A" "B" ...
 $ Mode_of_Shipment   : chr  "Flight" "Flight" "Flight" NA ...
 $ Customer_care_calls: int  4 4 2 3 2 3 NA 4 3 3 ...
 $ Customer_rating    : int  2 5 2 3 2 1 4 1 4 2 ...
 $ Cost_of_the_Product: int  177 216 183 176 NA 162 250 233 150 164 ...
 $ Prior_purchases    : int  3 2 4 4 3 3 3 2 3 3 ...
 $ Product_importance : chr  "low" "low" "low" "medium" ...
 $ Gender             : chr  "F" "M" "M" "M" ...
 $ Discount_offered   : int  NA 59 NA 10 46 12 3 48 NA 29 ...
 $ Weight_in_gms      : int  1233 NA 3374 1177 2484 1417 2371 2804 1861 1187 ...
 $ Reached.on.Time_Y.N: int  1 1 NA 1 1 1 1 1 1 1 ...
```

Figure 4.2: Internal structure of the dataset

Figure 4.2 shows the internal structure of the dataset. Few observations are identified and listed as followed:

- The dataset contains **10999 observations** and **12 variables**.
- The features that require encoding into **factor** are warehouse block, mode of shipment, gender, and reached on time.
- The feature product importance is an ordinal variable, it is suggested to perform **label encoding** on such variable.

4.1.2 Data Distribution of Categorical Variables

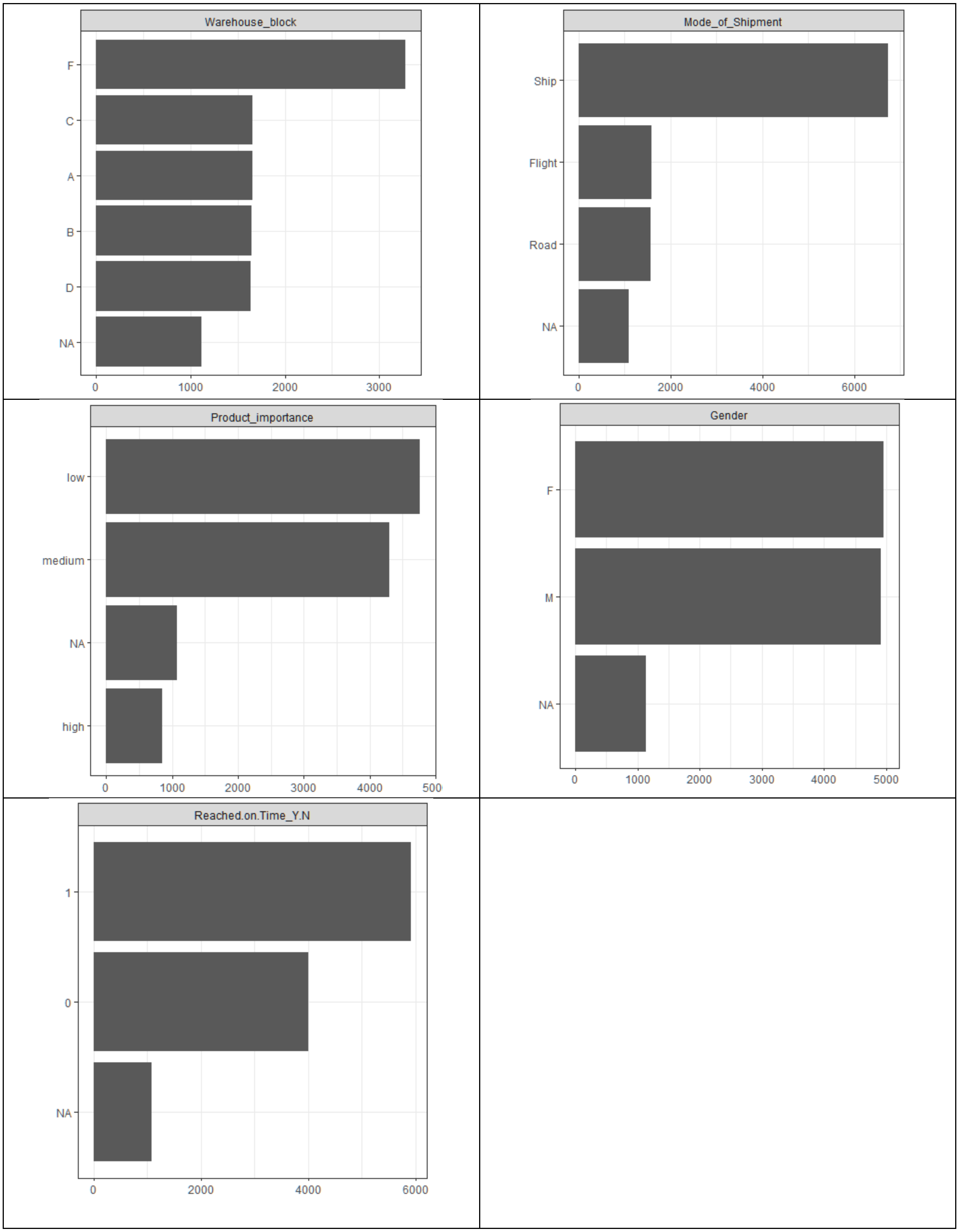

Figure 4.3: Data distribution of every categorical variable in the dataset

Figure 4.3 shows the data distribution of every categorical feature in dataset. The 'NA' observed in the bar chart of every feature indicates missing values which will not be discussed here. The vertical axis shows the categories available while the horizontal axis shows the frequency. This is applied to every bar chart in Figure 4.3. Observations of every feature will be listed as followed:

1. Warehouse block
    - As previously identified the presence of warehouse block 'F' which does not align with the metadata. **Recode** of the warehouse block 'F' into warehouse block 'E' will be performed.
    - Warehouse block 'F' is identified to be of the highest frequency with almost twice the amount as compared to other warehouse blocks.

2. Mode of shipment
    - The shipment mode using ships has the highest frequency as compared to flight and road. It is significantly more than the other mode of shipment with approximately over four times more as compared to others.

3. Product importance
    - Majority of the products fall under the low and medium importance which in total accounts for 90% of the total shipment.

4. Gender
    - The frequency of male and female is distributed almost equally.

5. Reached on time **(Target Variable)**
    - There is a higher number of products that did not reach on time as compared to products reaching on time.
    - The proportion of products did not reach on time is about **60%,** while products that reached on time is about **40%**. Therefore, no balancing of the dataset is required.

4.1.3 Data Distribution of Continuous Variables

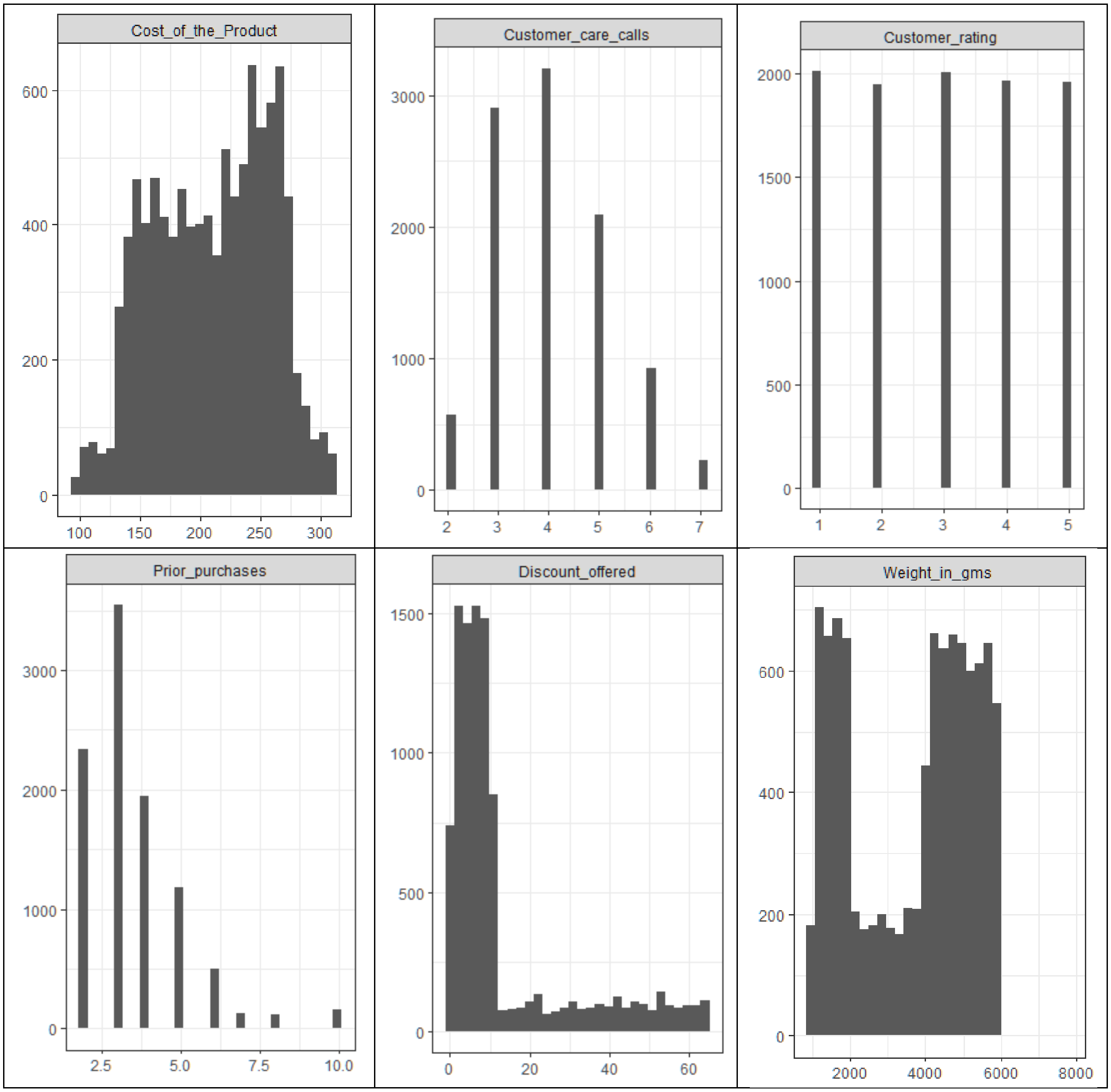

Figure 4.4: Data distribution of every numerical variable in the dataset

Figure 4.4 shows the data distribution of every numerical feature in dataset. The vertical axis shows the frequency while the horizontal axis shows the feature values. This is applied to every histogram in Figure 4.4. Observations of every feature will be listed as followed:

1. Cost of the product
   - Two major groups of product cost interval are identified to have high frequency.

- Majority of the product cost is between about 225 to about 275.
- Second major group of product cost is identified between about 140 to about 224.

2. Customer care call

- Majority of the customer called between three or four times to the customer care.

3. Customer rating

- There is not much variation between the ratings from one to five as provided by the customer.

4. Prior purchases

- Majority of the customers have three prior purchases count.

5. Discount offered

- Majority of the discount offered is between 2% to 8%.

6. Weight in grams

- Two major groups of product weight interval are identified to have high frequency.
- Majority of the product weight is between about 1000 to about 2000 grams.
- Second major group of product weight is identified between about 4000 to about 6000 grams.

4.1.4 Correlation Between Features

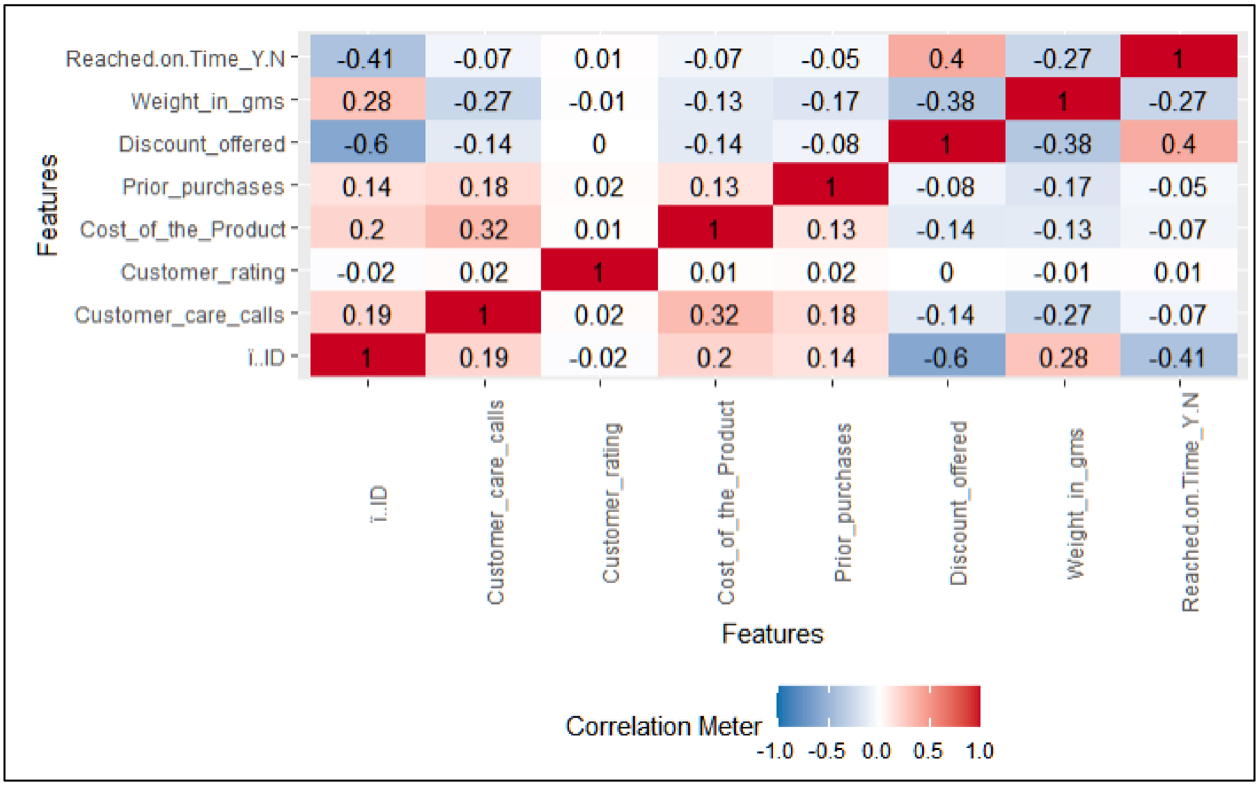

Figure 4.5: Correlation between features

Figure 4.5 shows the correlation matrix between numerical features. Observations from the correlation matrix are as followed:

- The discount offered has a medium positive correlation with the target variable reached on time with a correlation of 40%. A point increase in discount offered would imply a moderate increase in product reaching on time.
- Weight in grams has a weak negative correlation with the target variable reached on time with a correlation of -27%. A point increase in weight would imply a fair decrease in product reaching on time.
- Weight in grams has a weak negative correlation with customer care call frequency with a correlation of -27%. A point increase in weight would imply a fair decrease in customer care call frequency.
- Weight in grams has a medium negative correlation with discount offered with a correlation of -38%. A point increase in weight would imply a moderate decrease in discount offered.

- Cost of product has a medium positive correlation with customer care call frequency with a correlation of 32%. A point increase in cost of product would imply a moderate increase in customer care call frequency.

4.1.5 Identifying Missing Value

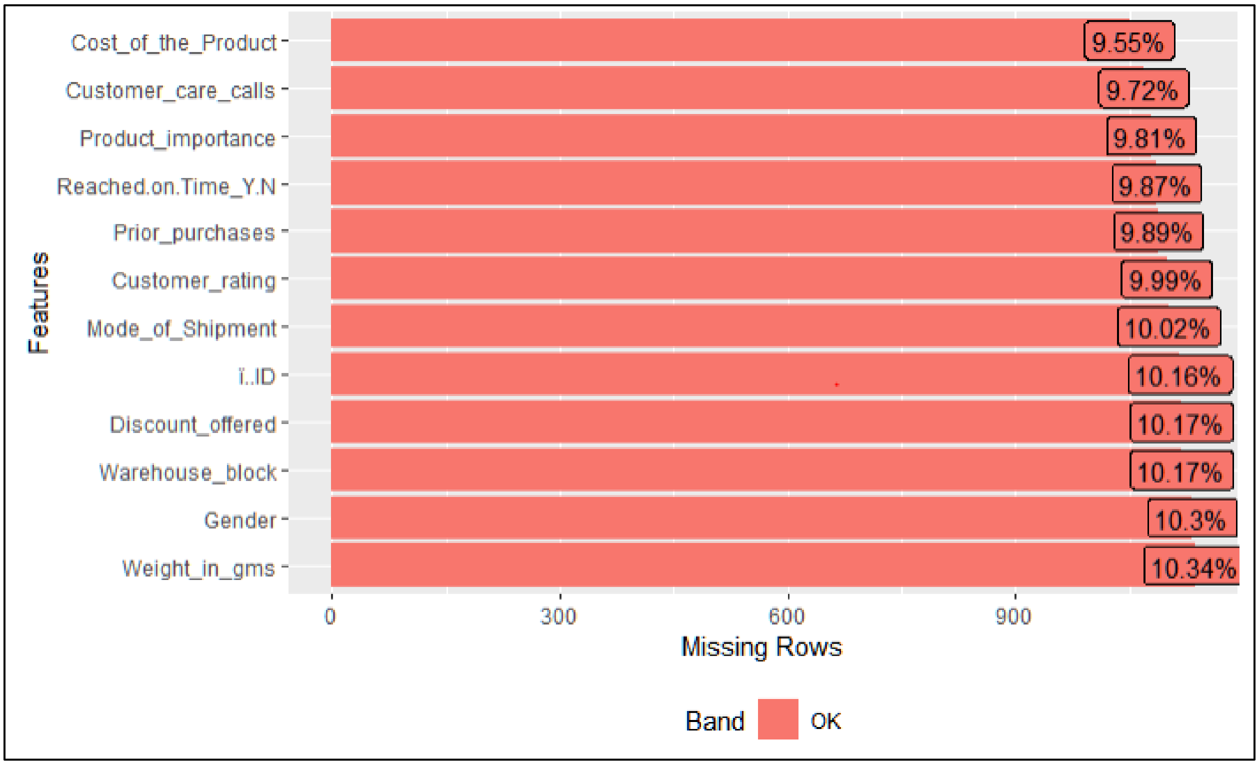

Figure 4.6: Missing values proportion

Figure 4.6 shows the proportion of missing values present in each feature. It is observed that all features have missing values and the proportion of missing values is about 10%. Since the proportion of missing value for every feature is low, **missing value imputation is suggested**. There is no need to drop any columns or rows.

4.2 DATA PRE-PROCESSING

4.2.1 Dropping and Recoding Features

The ID column will be dropped from the dataset as it is not informative in the model development stage. Figure 4.7 shows the internal structure of the dataset after dropping the ID column, leaving the dataset with 11 variables.

```
'data.frame':   10999 obs. of  11 variables:
 $ Warehouse_block    : chr  "D" "F" "A" "B" ...
 $ Mode_of_Shipment   : chr  "Flight" "Flight" "Flight" NA ...
 $ Customer_care_calls: int  4 4 2 3 2 3 NA 4 3 3 ...
 $ Customer_rating    : int  2 5 2 3 2 1 4 1 4 2 ...
 $ Cost_of_the_Product: int  177 216 183 176 NA 162 250 233 150 164 ...
 $ Prior_purchases    : int  3 2 4 4 3 3 3 2 3 3 ...
 $ Product_importance : chr  "low" "low" "low" "medium" ...
 $ Gender             : chr  "F" "M" "M" "M" ...
 $ Discount_offered   : int  NA 59 NA 10 46 12 3 48 NA 29 ...
 $ Weight_in_gms      : int  1233 NA 3374 1177 2484 1417 2371 2804 1861 1187 ...
 $ Reached.on.Time_Y.N: int  1 1 NA 1 1 1 1 1 1 1 ...
```

Figure 4.7: Internal structure of dataset after dropping

As previously mentioned, the need to recode the feature warehouse block ‘F’ into ‘E’. The recode function is used to recode the warehouse block ‘F’ values into ‘E’. Table 4.1 shows the frequency of each warehouse block after recoding. In addition, the feature product importance which is an ordinal variable is recoded with the following encodings shown in Table 4.2.

Table 4.1: Frequency table of warehouse block after recoding

Warehouse block	A	B	C	D	E
Frequency	1659	1649	1661	1636	3275

Table 4.2: Recoding for product importance

Original value	**Recoded value**
Low	1
Medium	2
High	3

4.2.2 Factoring Categorical Variables

As previously mentioned, four categorical features will be converted to factor. The as.factor function is used to convert the categorical features into a factor. Figure 4.8 shows the internal structure of the dataset after converting categorical features into factor.

```
'data.frame':   10999 obs. of  11 variables:
 $ Warehouse_block    : Factor w/ 5 levels "A","B","C","D",..: 4 5 1 2 3 5 4 5 1 2 ...
 $ Mode_of_Shipment   : Factor w/ 3 levels "Flight","Road",..: 1 1 1 NA 1 1 1 NA 1 1 ...
 $ Customer_care_calls: int  4 4 2 3 2 3 NA 4 3 3 ...
 $ Customer_rating    : int  2 5 2 3 2 1 4 1 4 2 ...
 $ Cost_of_the_Product: int  177 216 183 176 NA 162 250 233 150 164 ...
 $ Prior_purchases    : int  3 2 4 4 3 3 3 2 3 3 ...
 $ Product_importance : int  1 1 1 2 NA 2 1 1 1 2 ...
 $ Gender             : Factor w/ 2 levels "F","M": 1 2 2 2 1 1 1 NA NA 1 ...
 $ Discount_offered   : int  NA 59 NA 10 46 12 3 48 NA 29 ...
 $ Weight_in_gms      : int  1233 NA 3374 1177 2484 1417 2371 2804 1861 1187 ...
 $ Reached.on.Time_Y.N: Factor w/ 2 levels "0","1": 2 2 NA 2 2 2 2 2 2 2 ...
```

Figure 4.8: Internal structure of dataset after factor

Based on Figure 4.8 the following observations are identified and listed as followed:

- The feature warehouse block after applying factor contains five levels.
- The feature mode of shipment after applying factor contains three levels.
- The feature gender after applying factor contains two levels.
- The feature reached on time after applying factor contains two levels.

4.2.3 Missing Value Imputation

The missing values present in the dataset is imputed using the mice package. Figure 4.9 shows the proportion of missing values after imputation. Based on the figure, all features now have zero missing values.

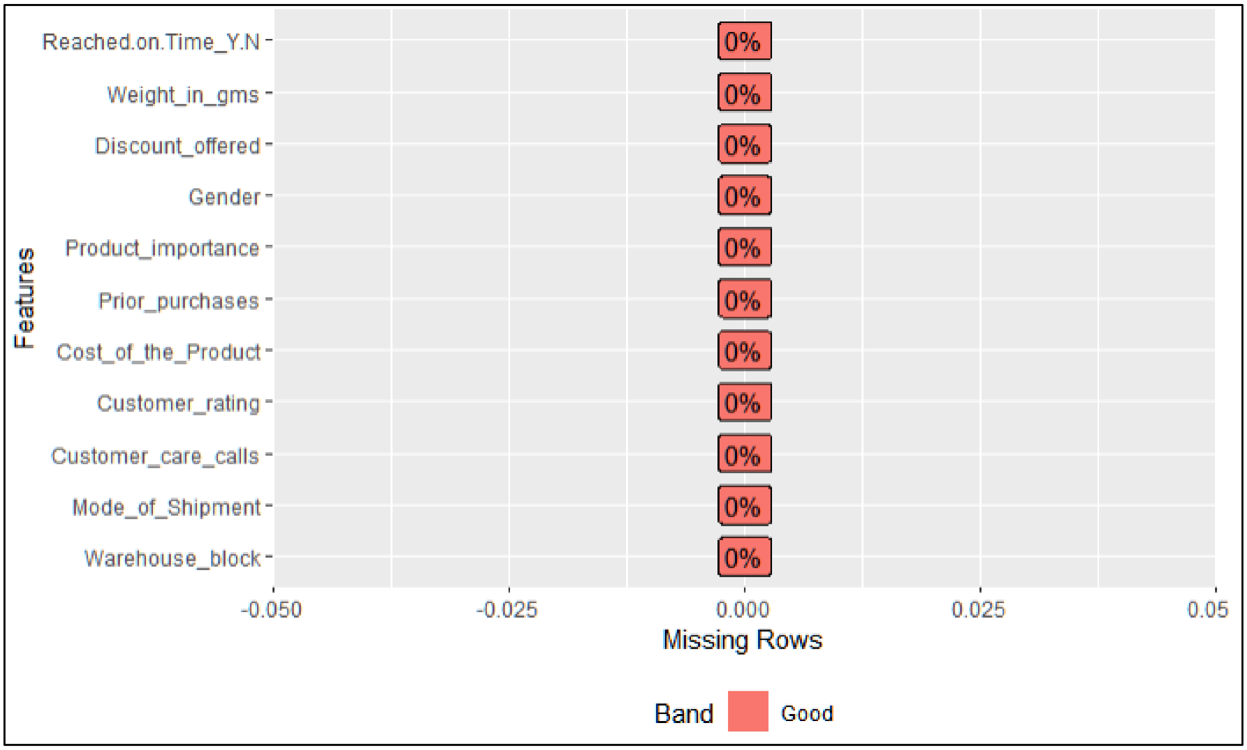

Figure 4.9: Missing value imputation result

4.2.4 Feature Encoding

Two types of feature encoding are performed namely label encoding and one-hot encoding. Label encoding is performed on the feature gender as the values are only binary which is redundant if applied one-hot encoding. One-hot encoding is applied using dummify function from the DataExplorer package. Figure 4.10 shows the internal structure of the dataset after feature encoding.

```
'data.frame':   10999 obs. of  17 variables:
 $ Customer_care_calls    : int  4 4 2 3 2 3 5 4 3 3 ...
 $ Customer_rating        : int  2 5 2 3 2 1 4 1 4 2 ...
 $ Cost_of_the_Product    : int  177 216 183 176 201 162 250 233 150 164 ...
 $ Prior_purchases        : int  3 2 4 4 3 3 3 2 3 3 ...
 $ Product_importance     : num  1 1 1 2 1 2 1 1 1 2 ...
 $ Gender                 : num  1 0 0 0 1 1 1 1 1 1 ...
 $ Discount_offered       : int  42 59 23 10 46 12 3 48 32 29 ...
 $ Weight_in_gms          : int  1233 1645 3374 1177 2484 1417 2371 2804 1861 1187 ...
 $ Reached.on.Time_Y.N    : Factor w/ 2 levels "On Time","Not on Time": 2 2 2 2 2 2 2 2 2 2 ...
 $ Warehouse_block_A      : int  0 0 1 0 0 0 0 0 1 0 ...
 $ Warehouse_block_B      : int  0 0 0 1 0 0 0 0 0 1 ...
 $ Warehouse_block_C      : int  0 0 0 0 1 0 0 0 0 0 ...
 $ Warehouse_block_D      : int  1 0 0 0 0 0 1 0 0 0 ...
 $ Warehouse_block_E      : int  0 1 0 0 0 1 0 1 0 0 ...
 $ Mode_of_Shipment_Flight: int  1 1 1 0 1 1 1 1 1 1 ...
 $ Mode_of_Shipment_Road  : int  0 0 0 0 0 0 0 0 0 0 ...
 $ Mode_of_Shipment_Ship  : int  0 0 0 1 0 0 0 0 0 0 ...
```

Figure 4.10: Internal structure after feature encoding

Based on Figure 4.10 the following observations are identified and listed as followed:

- The feature warehouse block is one-hot encoded and divided into five features, each representing one warehouse block.
- The feature mode of shipment is one-hot encoded and divided into three features, each representing one mode of shipment.
- The total number of variables is now increased to 17 variables.

4.2.5 Feature scaling

Feature scaling is performed since the range of values of the dataset varies widely. Normalization is applied for scaling the features to confine the value range between zero and one. This is performed to achieve better model convergence. Figure 4.11 shows the summary statistics of the features after applying feature scaling. The preProcess function from the caret package is utilized to perform the feature scaling with the parameter ‘method’ set as ‘range’ to perform normalization on features.

```
Customer_care_calls Customer_rating  Cost_of_the_Product Prior_purchases  Product_importance     Gender        Discount_offered
Min.   :0.0000      Min.   :0.0000   Min.   :0.0000      Min.   :0.0000   Min.   :0.0000     Min.   :0.0000   Min.   :0.00000
1st Qu.:0.2000      1st Qu.:0.2500   1st Qu.:0.3458      1st Qu.:0.1250   1st Qu.:0.0000     1st Qu.:0.0000   1st Qu.:0.04688
Median :0.4000      Median :0.5000   Median :0.5514      Median :0.1250   Median :0.5000     Median :1.0000   Median :0.09375
Mean   :0.4121      Mean   :0.4997   Mean   :0.5339      Mean   :0.1963   Mean   :0.3013     Mean   :0.5025   Mean   :0.19393
3rd Qu.:0.6000      3rd Qu.:0.7500   3rd Qu.:0.7243      3rd Qu.:0.2500   3rd Qu.:0.5000     3rd Qu.:1.0000   3rd Qu.:0.14062
Max.   :1.0000      Max.   :1.0000   Max.   :1.0000      Max.   :1.0000   Max.   :1.0000     Max.   :1.0000   Max.   :1.00000
Weight_in_gms         Reached.on.Time_Y.N Warehouse_block_A Warehouse_block_B Warehouse_block_C Warehouse_block_D Warehouse_block_E
Min.   :0.0000      On Time    :4454      Min.   :0.0000    Min.   :0.0000    Min.   :0.0000    Min.   :0.0000    Min.   :0.0000
1st Qu.:0.1243      Not on Time:6545      1st Qu.:0.0000    1st Qu.:0.0000    1st Qu.:0.0000    1st Qu.:0.0000    1st Qu.:0.0000
Median :0.4603                            Median :0.0000    Median :0.0000    Median :0.0000    Median :0.0000    Median :0.0000
Mean   :0.3857                            Mean   :0.1701    Mean   :0.1683    Mean   :0.1663    Mean   :0.1657    Mean   :0.3297
3rd Qu.:0.5918                            3rd Qu.:0.0000    3rd Qu.:0.0000    3rd Qu.:0.0000    3rd Qu.:0.0000    3rd Qu.:1.0000
Max.   :1.0000                            Max.   :1.0000    Max.   :1.0000    Max.   :1.0000    Max.   :1.0000    Max.   :1.0000
Mode_of_Shipment_Flight Mode_of_Shipment_Road Mode_of_Shipment_Ship
Min.   :0.0000          Min.   :0.0000        Min.   :0.0000
1st Qu.:0.0000          1st Qu.:0.0000        1st Qu.:0.0000
Median :0.0000          Median :0.0000        Median :1.0000
Mean   :0.1611          Mean   :0.1582        Mean   :0.6807
3rd Qu.:0.0000          3rd Qu.:0.0000        3rd Qu.:1.0000
Max.   :1.0000          Max.   :1.0000        Max.   :1.0000
```

Figure 4.11: Summary statistics of features after feature scaling

Based on Figure 4.11 the following observations are identified and listed as followed:

- All features now have a value range between zero and one.
- The target variable reached on time remains as a factor.

4.2.6 Train and Test Data Split

The data is split into two subsets namely training set and testing set. The training set will be used for fitting the model while the testing set will be used for validation. The split ratio adopted for the dataset is 80% allocated to the training set and 20% allocated to the testing set. The data split is performed using sample.split function from the caTools package which preserve the relative ratio of the class labels. Table 4.3 shows the target variable class frequency after applying the data split.

Table 4.3: Class frequency of train and test set

	Class frequency		Total
	On Time	**Not on Time**	
Training Set	3563	5236	8799
Testing Set	891	1309	2200

Based on Table 4.3 the following observations are identified and listed as followed:

- The proportion of each class after splitting remained the same as the original dataset which is about 40% for the On Time class and 60% for the Not on Time class.
- 80% of the total observations falls into the training set with a total 8799 observations.
- 20% of the total observations falls into the testing set with a total 2200 observations.

SECTION 5

MODEL IMPLEMENTATION

Four machine learning algorithms are chosen and implemented to identify the best performer to be compared to related literature. The model development process will be discussed in this section which include model fitting to training data subset, validation by testing data subset, and evaluation metric computation for evaluating the performance of each model. All models will be built using the caret package.

Each of the algorithm used to develop the model would consist of a base model with hyperparameters settings as default and an optimized model where hyperparameter tuning is applied. The prediction task is a classifier that predicts the delivery time of the package with output either as delivery is on time or not on time.

5.1 LOGISTIC REGRESSION

Since logistic regression does not have any hyperparameters for tuning thus only one model is developed. The performance of the logistic regression model will serve as a benchmark to the other models in this study.

5.1.1 Logistic Regression with Cross Validation

The logistic regression model is built using the generalized linear model method from the caret package. A 10-fold repeated cross validation (CV) is applied to the fitting model. Figure 5.1 shows a snippet of the code used for developing the model.

```
# Train set
tc1_2 = trainControl(method='repeatedcv',number = 10, repeats = 3)
cls1_2 = train(Reached.on.Time_Y.N ~., data = trainSet, method = "glm",metric = 'Accuracy',family = binomial, trControl = tc1_2)
summary(cls1_2)

predTrain1_2 = predict(cls1_2, subset(trainSet, select = -(Reached.on.Time_Y.N)))
# Test set
predTest1_2 = predict(cls1_2, subset(testSet, select = -(Reached.on.Time_Y.N)))
```

Figure 5.1: Logistic regression model with cross validation snippet

5.1.2 Logistic Regression Model Performance

The logistic regression model performance will be discussed in this section. Table 5.1 shows the confusion matrix for the logistic regression model at training and testing stage. These results are further processed to calculate for other evaluation metrics. Table 5.2 shows the evaluation metrics computed based on the confusion matrix of the model.

Table 5.1: Confusion matrix for logistic regression model

	Train Set			Test Set		
Base Model	Reference / Prediction	**On Time**	**Not on Time**	Reference / Prediction	**On Time**	**Not on Time**
	On Time	2151	1606	**On Time**	519	398
	Not on Time	1412	3630	**Not on Time**	372	911

Table 5.2: Evaluation metric results for logistic regression model

	Base Model	
	Train Set	**Test Set**
Accuracy	0.6570	0.6500
Kappa	0.2944	0.2772
Sensitivity	0.6037	0.5825
Specificity	0.6933	0.6960

Based on Table 5.2, the following observations are identified and listed as followed:

- Accuracy on training set obtained 65.7% which is slightly higher than the testing set of 65%. The difference is small which indicates model is a good fit.
- Kappa on the testing set obtained 0.2772 which indicates a fair agreement in the predictive performance.
- Sensitivity on the testing set obtained 0.5825 which indicates model is moderately accurate in correctly classifying positive outcomes.
- Specificity on the testing set obtained 0.6960 which indicates model has good accuracy in correctly classifying negative outcomes.

Figure 5.2 shows the comparison of Receiver Operating Characteristic (ROC) curve for the logistic regression model for the training data and testing data. The area under the ROC curve is computed and labeled in each diagram. It is observed that the testing data area under ROC is 0.6390 which is slightly lower than the training data of 0.6480. This indicates model has a good fit but model has weak performance in identifying the positive and negative class.

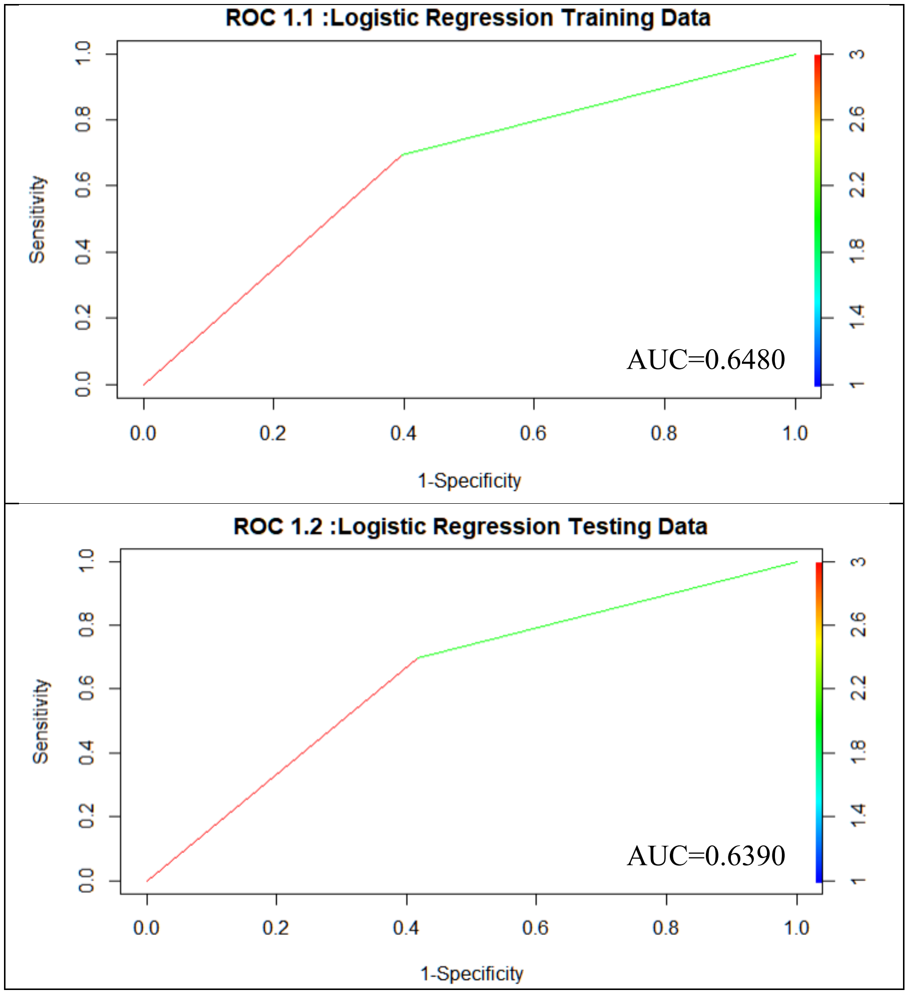

Figure 5.2: ROC curve for basic logistic regression

5.2 EXTREME GRADIENT BOOSTING (XGBOOST)

Two models are developed based on the XGBoost algorithm. First model is a basic model that adopts a fixed and default hyperparameter setting while the second model undergoes hyperparameter optimization to identify best performing model.

5.2.1 Basic XGBoost model

The basic XGBoost model is built using xgbTree method from caret. The following list the hyperparameters along with their description. These hyperparameter values are the default values and will be fixed when fitting the model. Figure 5.3 shows a snippet of basic XGBoost model building and fitting to the training and testing set.

- ‘eta’: Learning rate = 0.3
- ‘gamma’: Minimum loss reduction = 0
- ‘max_depth’: Maximum depth of tree = 6
- ‘subsample’: Subsample ratio of training instances = 1
- ‘colsample_bytree’: Subsample ratio of columns when constructing each tree = 1
- ‘min_child_weight’: Minimum sum of instance weight needed in a child = 1
- ‘nrounds’: Number of trees in the final model = 100

```
grid = expand.grid(eta=0.3, nrounds=100, max_depth=6, gamma=0, colsample_bytree =1, min_child_weight=1, subsample=1)
cls2_1 = train(Reached.on.Time_Y.N~., data=trainSet, method="xgbTree", tuneGrid = grid, metric='Accuracy')
# Training set
predTrain2_1 = predict(cls2_1, trainSet)
# Testing set
predTest2_1 = predict(cls2_1, testSet)
```

Figure 5.3: Snippet of basic XGBoost model building and fitting

5.2.2 Optimized XGBoost model

The optimized XGBoost model is built using xgbTree method from caret. The optimization of the XGBoost model is performed using grid search method on a range of hyperparameter values. In addition, 10-fold repeated CV is applied to the fitting model during the hyperparameter optimization process. The hyperparameter value ranges for the grid search are listed as followed:

- ‘eta’: 0.0.5
- ‘gamma’: from 0.1 to 1 with step 0.1
- ‘max_depth’: from 5 to 10 with step 1
- ‘subsample’: 0.5
- ‘colsample_bytree’: 0.5
- ‘min_child_weight’: from 1 to 20 with step 2
- ‘nrounds’: from 50 to 200 with step 50

Based on the range of hyperparameter values, 2640 combinations of hyperparameter value settings are generated which the model would iterate through to identify the best performing hyperparameter value combination. Results from each iteration will be attached under Appendix A. Following that, a XGBoost model will be built upon the best performing hyperparameter value combination. Figure 5.4 shows a snippet of XGBoost model with grid search of the selected hyperparameter ranges and fitted to the training and testing set. The best performing hyperparameter combination identified are as followed:

- ‘eta’: 0.05
- ‘gamma’: 0.6
- ‘max_depth’: 5
- ‘subsample’: 0.5
- ‘colsample_bytree’: 0.5
- ‘min_child_weight’: 15
- ‘nrounds’: 50

```
tc2_2 = trainControl(method="repeatedcv", number=10, repeats=3, allowParallel = T, verboseIter = F)
grid=expand.grid(eta = 0.05,
                  max_depth = seq(5,10,1),
                  gamma = seq(0,1,0.1),
                 subsample = 0.5,
                 colsample_bytree = 0.5,
                  min_child_weight= seq(1,20,2),
                 nrounds = seq(50,200,50))

cls2_2 = train(Reached.on.Time_Y.N~., data=trainSet, method="xgbTree", trControl=tc2_2, tuneGrid =grid, metric='Accuracy', verbosity=0)
# Training set
predTrain2_2 = predict(cls2_2, trainSet)
# Testing set
predTest2_2 = predict(cls2_2, testSet)
```

Figure 5.4: Snippet of optimized XGBoost model building and fitting

5.2.3 XGBoost Model Performance

The model performance before and after applying hyperparameter optimization for the XGBoost models will be discussed in this section. Table 5.3 shows the confusion matrix for both the XGBoost models at training and testing stage. The results are used to calculate the evaluation metrics. Table 5.4 shows the evaluation metrics computed based on the confusion matrix for the XGBoost models.

Table 5.3: Confusion matrix for XGBoost models

	Train Set			Test Set		
Base Model	**Reference / Prediction**	**On Time**	**Not on Time**	**Reference / Prediction**	**On Time**	**Not on Time**
	On Time	3333	574	**On Time**	580	405
	Not on Time	230	4662	**Not on Time**	311	904
Optimized Model	**Reference / Prediction**	**On Time**	**Not on Time**	**Reference / Prediction**	**On Time**	**Not on Time**
	On Time	2954	1962	**On Time**	706	512
	Not on Time	609	3274	**Not on Time**	185	797

Table 5.4: Evaluation metric results for XGBoost models

	Base Model		Optimized Model	
	Train Set	**Test Set**	**Train Set**	**Test Set**
Accuracy	0.9086	0.6745	0.7078	0.6832
Kappa	0.8133	0.3359	0.4284	0.3790
Sensitivity	0.9354	0.6510	0.8291	0.7924
Specificity	0.8531	0.6906	0.6253	0.6089

Based on Table 5.4, the following observations are identified and listed as followed:

- The accuracy of the optimized model is higher as compared to the base model which obtained 68.32% and 67.45% respectively. This indicates the hyperparameter optimization has obtained a better performance model.
- The accuracy between the training and testing set for the base model has a wide difference which indicates model is overfitting. However, in the optimized model, the difference was small, which indicates model has a good fit.
- Kappa for both the models have fair agreement in the predictive performance.
- Sensitivity for the base model obtained 0.6510 which indicates model has moderate accuracy in correctly classifying positive outcomes. However, in the optimized model which obtained 0.7924 indicates model has good accuracy in correctly classifying positive outcomes.
- Specificity for the base model obtained 0.6906 which indicates moderate accuracy in correctly classifying negative outcomes. Similarly, in the optimized model which obtained 0.6089 indicates model has moderate accuracy in correctly classifying negative outcomes.

Figure 5.5 shows the comparison of ROC curve for the basic XGBoost model in the training and testing data. The area under the ROC curve is computed and labeled in each diagram. It is observed that the testing data area under ROC is 0.671 which is lower than the training data of 0.913. This indicates the model is slightly overfitting but provides acceptable performance in identifying the positive and negative class.

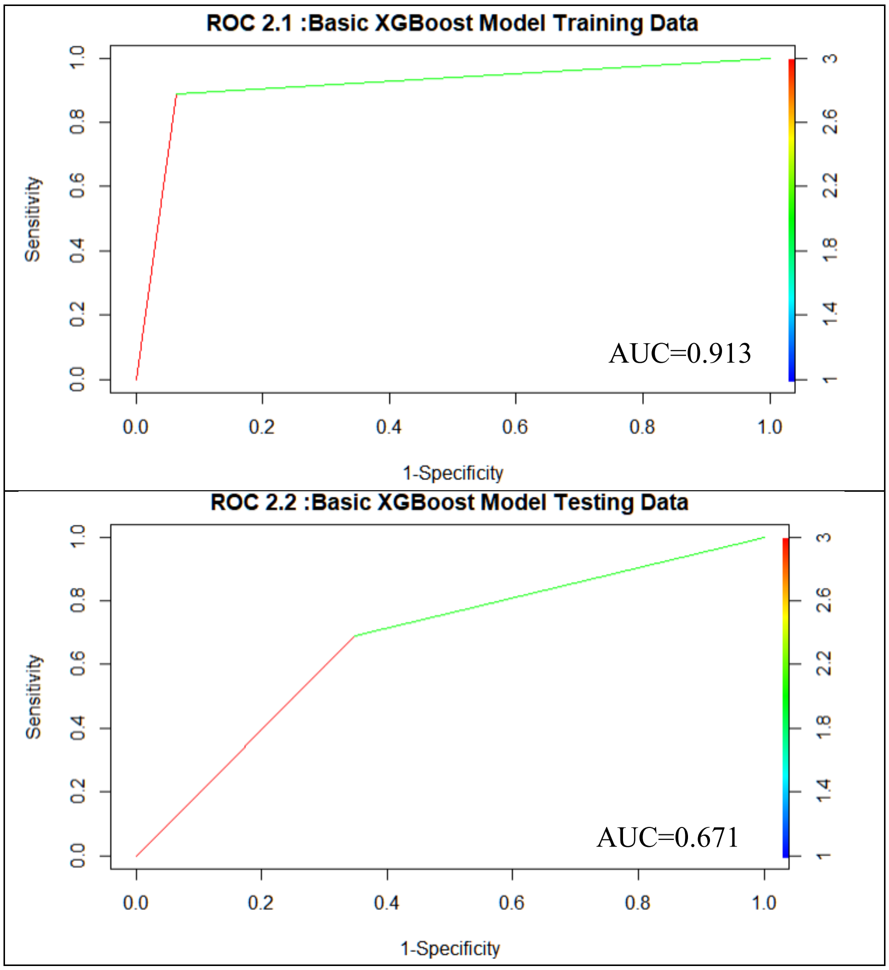

Figure 5.5: ROC curve for basic XGBoost

Figure 5.6 shows the comparison of ROC curve for the optimized XGBoost model in the training and testing data. The area under the ROC curve is computed and labeled in each diagram. It is observed that the testing data area under ROC is 0.701 which is slightly lower than the training data of 0.727. This indicates model is good fit and provides acceptable model performance in identifying the positive and negative class.

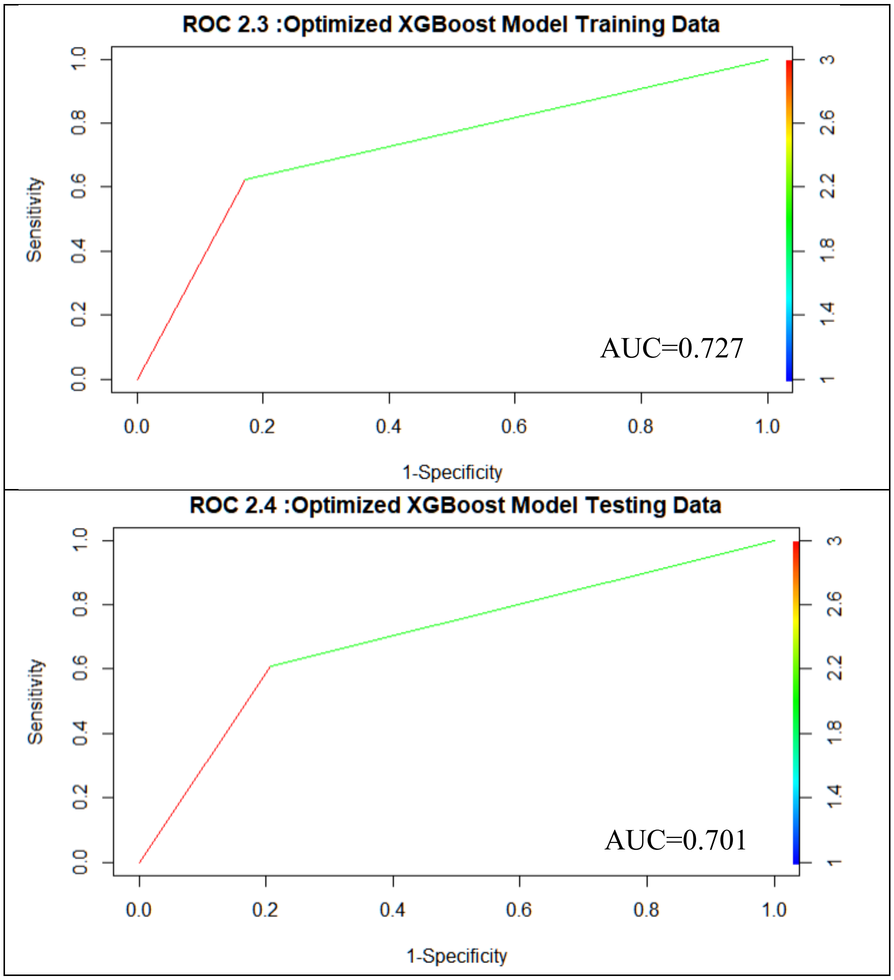

Figure 5.6: ROC curve for optimized XGBoost

5.3 ADAPTIVE BOOSTING (ADABOOST)

Two models are developed based on the AdaBoost algorithm. First model is a basic model that adopts a fixed and default hyperparameter setting while the second model undergoes hyperparameter optimization to identify best performing model.

5.3.1 Basic AdaBoost Model

The basic AdaBoost model is built using AdaBag method from caret. The following list the hyperparameters along with their description. These hyperparameter values are the default values and will be fixed when fitting the model. Figure 5.7 shows a snippet of basic AdaBoost model building and fitting to the training and testing set.

- ‘mfinal’: Number of trees = 50

- ‘maxdepth’: Maximum tree depth = 1

```
grid = expand.grid(mfinal=50, maxdepth=1)
cls4 = train(Reached.on.Time_Y.N~., data=trainSet, method="AdaBag", tuneGrid = grid, metric='Accuracy')
# Training data
predTrain4_1 = predict(cls4,trainSet)
# Testing data
predTest4_1 = predict(cls4,testSet)
```

Figure 5.7: Snippet of basic AdaBoost model building and fitting

5.3.2 Optimized AdaBoost Model

The optimized Adaboost model is built using AdaBag method from caret. The optimization of the AdaBoost model is performed using grid search method on a range of hyperparameter values. In addition, 10-fold repeated CV is applied to the fitting model during the hyperparameter optimization process. The hyperparameter value ranges for the grid search are listed as followed:

- ‘mfinal’: from 50 to 500 with step 50
- ‘maxdepth’: from 1 to 10 with step 1

Based on the range of hyperparameter values, 100 combinations of hyperparameter value settings are generated which the model would iterate through to identify the best performing hyperparameter value combination. Results from each iteration will be attached under Appendix A. Following that, an AdaBoost model will be built upon the best performing hyperparameter value combination. Figure 5.8 shows a snippet of AdaBoost model with grid search of the selected hyperparameter ranges and fitted to the training and testing set. The best performing hyperparameter combination identified are as followed:

- ‘mfinal’: 200
- ‘maxdepth’: 5

```
tc4_2 = trainControl(method="repeatedcv", number=10, repeats=3, allowParallel = T)
metric = "Accuracy"
set.seed(globalSeed)

grid=expand.grid(mfinal = seq(50,500,50), maxdepth=seq(1,10,1))
cls4_2 = train(Reached.on.Time_Y.N~., data=trainSet, method="AdaBag", trControl=tc4_2, tuneGrid =grid )
# Training set
predTrain4_2 = predict(cls4_2, trainSet)
# Testing set
predTest4_2 = predict(cls4_2, testSet)
```

Figure 5.8: Snippet of optimized AdaBoost model building and fitting

5.3.3 AdaBoost Model Performance

The model performance before and after applying hyperparameter optimization for the AdaBoost models will be discussed in this section. Table 5.5 shows the confusion matrix for both the AdaBoost models at training and testing stage. The results are used to calculate the evaluation metrics. Table 5.6 shows the evaluation metrics computed based on the confusion matrix for the AdaBoost models.

Table 5.5: Confusion matrix for AdaBoost models

	Train Set			**Test Set**		
Base Model	**Reference / Prediction**	**On Time**	**Not on Time**	**Reference / Prediction**	**On Time**	**Not on Time**
	On Time	3540	3148	**On Time**	889	770
	Not on Time	23	2088	**Not on Time**	2	539
Optimized Model	**Reference / Prediction**	**On Time**	**Not on Time**	**Reference / Prediction**	**On Time**	**Not on Time**
	On Time	3342	2480	**On Time**	833	606
	Not on Time	221	2756	**Not on Time**	58	703

Table 5.6: Evaluation metric results for AdaBoost models

	Base Model		**Optimized Model**	
	Train Set	**Test Set**	**Train Set**	**Test Set**
Accuracy	0.6396	0.6491	0.6930	0.6982
Kappa	0.3441	0.3600	0.4216	0.4298
Sensitivity	0.9935	0.9978	0.9380	0.9349
Specificity	0.3988	0.4118	0.5264	0.5371

Based on Table 5.6, the following observations are identified and listed as followed:

- The accuracy of the optimized model is higher as compared to the base model which obtained 69.82% and 64.91% respectively. This indicates the hyperparameter optimization has obtained a better performance model.
- The accuracy of the testing set is higher than the training set for both the models which indicates model is slightly underfitting.
- Kappa for both the models have fair agreement in the predictive performance.
- Sensitivity for both the models obtained near perfect score which indicates outstanding accuracy of the model in correctly classifying positive outcomes.
- Specificity for both the models obtained a moderate score which indicates moderate accuracy of the model in correctly classifying negative outcomes.

Figure 5.9 shows the comparison of ROC curve for the basic AdaBoost model in the training and testing data. The area under the ROC curve is computed and labeled in each diagram. It is observed that the testing data area under ROC is 0.705 which is slightly higher than the training data of 0.696. This indicates model is slightly underfitting but an acceptable performance of the model in identifying the positive and negative class.

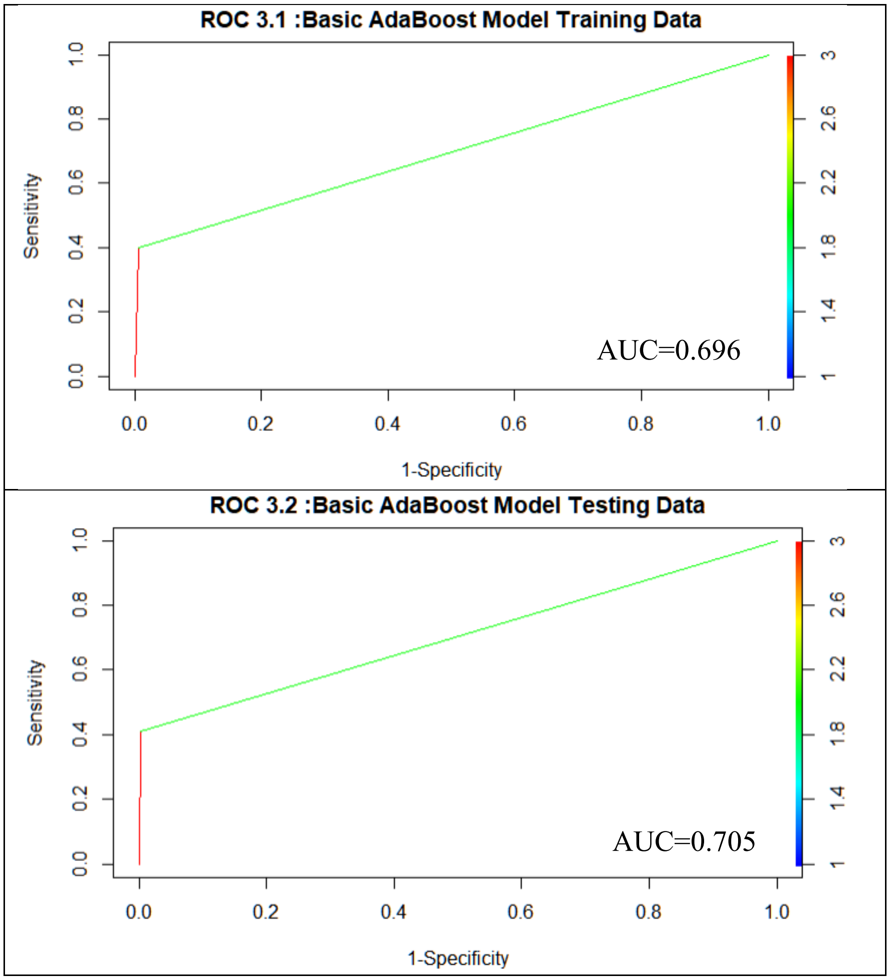

Figure 5.9: ROC curve for basic AdaBoost

Figure 5.10 shows the comparison of ROC curve for the optimized AdaBoost model in the training and testing data. The area under the ROC curve is computed and labeled in each diagram. It is observed that the testing data area under ROC is 0.736 which is just few points higher than the training data of 0.732. This indicates model is slightly underfitting but an acceptable performance of the model in identifying the positive and negative class.

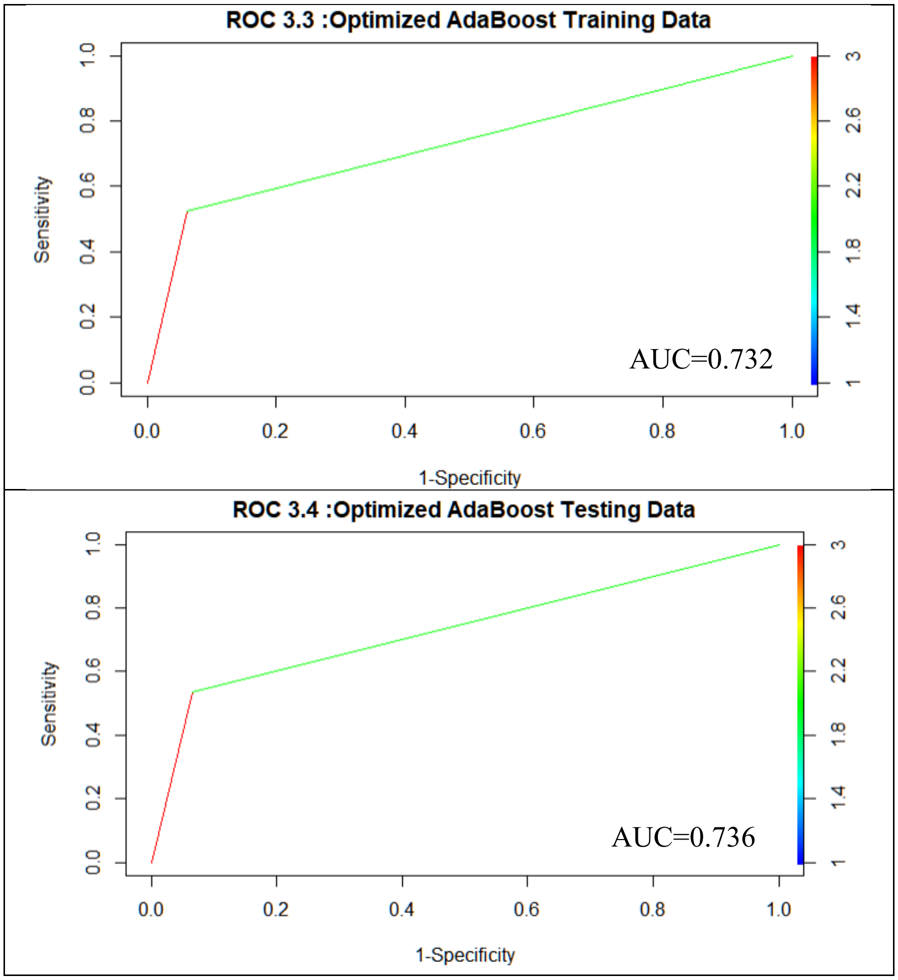

Figure 5.10: ROC curve for optimized AdaBoost

5.4 RANDOM FOREST

Two models are developed based on the Random Forest algorithm. First model is a basic model that adopts a fixed and default hyperparameter setting while the second model undergoes hyperparameter optimization to identify best performing model.

5.4.1 Basic Random Forest Model

The basic RF model is built using rf method from caret. The following list the hyperparameter along with the description. The hyperparameter value is the default value and will be fixed when fitting the model. Figure 5.11 shows a snippet of basic RF model building and fitting to the training and testing set.

- 'mtry': Random sampling of number of variables = 1

```
grid = expand.grid(mtry=1)
cls5 = train(Reached.on.Time_Y.N~., data=trainSet, method="rf", metric='Accuracy', tuneGrid=grid)

# Training set
predTrain5_1 = predict(cls5, trainSet)
# Testing set
predTest5_1 = predict(cls5,testSet)
```

Figure 5.11: Snippet of basic Random Forest model building and fitting

5.4.2 Optimized Random Forest Model

The optimized RF model is built using rf method from caret. The optimization of the RF model is performed using grid search method on a range of hyperparameter values. In addition, 10-fold repeated CV is applied to the fitting model during hyperparameter optimization process. The hyperparameter value range for the grid search is listed as followed:

- 'mtry': from 1 to 17 with step 1

Based on the range of hyperparameter values, 17 combinations of hyperparameter value settings are generated which the model would iterate through to identify the best performing hyperparameter value. Results from each iteration will be attached under Appendix A. Following that, a RF model will be built upon the best performing hyperparameter. Figure 5.12 shows a snippet of RF model with grid search of the selected hyperparameter ranges and fitted to the training and testing set. The best performing hyperparameter identified is as followed:

- 'mtry': 2

```
tc5_2 = trainControl(method="repeatedcv", number=10, repeats=3)
set.seed(globalSeed)
tunegrid = expand.grid(mtry=seq(1:17))

cls5_2 = train(Reached.on.Time_Y.N~., data=trainSet, method="rf", metric='Accuracy', tuneGrid=tunegrid, trControl=tc5_2)
# Training set
predTrain5_2 = predict(cls5_2, trainSet)
# Testing set
predTest5_2 = predict(cls5_2, testSet)
```

Figure 5.12: Snippet of optimized Random Forest model building and fitting

5.4.3 Random Forest Model Performance

The model performance before and after applying hyperparameter optimization for the RF models will be discussed in this section. Table 5.7 shows the confusion matrix for both the RF models at training and testing stage. The results are used to calculate the evaluation metrics. Table 5.8 shows the evaluation metrics computed based on the confusion matrix for the RF models.

Table 5.7: Confusion matrix for RF models

	Train Set			**Test Set**		
Base Model	**Prediction \ Reference**	**On Time**	**Not on Time**	**Prediction \ Reference**	**On Time**	**Not on Time**
	On Time	595	86	**On Time**	81	52
	Not on Time	2968	5150	**Not on Time**	810	1257
Optimized Model	**Prediction \ Reference**	**On Time**	**Not on Time**	**Prediction \ Reference**	**On Time**	**Not on Time**
	On Time	3323	949	**On Time**	683	480
	Not on Time	240	4287	**Not on Time**	208	829

Table 5.8: Evaluation metric results for Random Forest models

	Base Model		**Optimized Model**	
	Train Set	**Test Set**	**Train Set**	**Test Set**
Accuracy	0.6529	0.6082	0.8649	0.6873
Kappa	0.1729	0.0592	0.7282	0.3813
Sensitivity	0.1670	0.0909	0.9326	0.7666
Specificity	0.9836	0.9603	0.8188	0.6333

Based on Table 5.8, the following observations are identified and listed as followed:

- The accuracy of the optimized model is higher as compared to the base model which obtained 68.73% and 60.82% respectively. This indicates the hyperparameter optimization has obtained a better performance model.
- The accuracy of the testing set is slightly lower than the training set for both the models which indicates model is slightly overfitting.
- Kappa for the base model obtained a poor agreement in the predictive performance. However, for the optimized model the kappa obtained a fair agreement in the predictive performance.
- Sensitivity for the base model is extremely poor which indicates poor accuracy for the model in correctly classifying positive outcomes. However, in the optimized model the sensitivity is high which indicates model is good at correctly classifying positive outcomes.

- Specificity for the base model is near perfect which indicates very high accuracy for the model in correctly classifying negative outcomes. However, in the optimized model the specificity is moderate which indicates moderate accuracy of the model in correctly classifying negative outcomes.

Figure 5.13 shows the comparison of ROC curve for the basic RF model in the training and testing data. The area under the ROC curve is computed and labeled in each diagram. It is observed that the training data area under ROC is 0.575 which is slightly higher than the testing data of 0.526. This indicates model is a good fit, but the model is showing weak performance in identifying the positive and negative class.

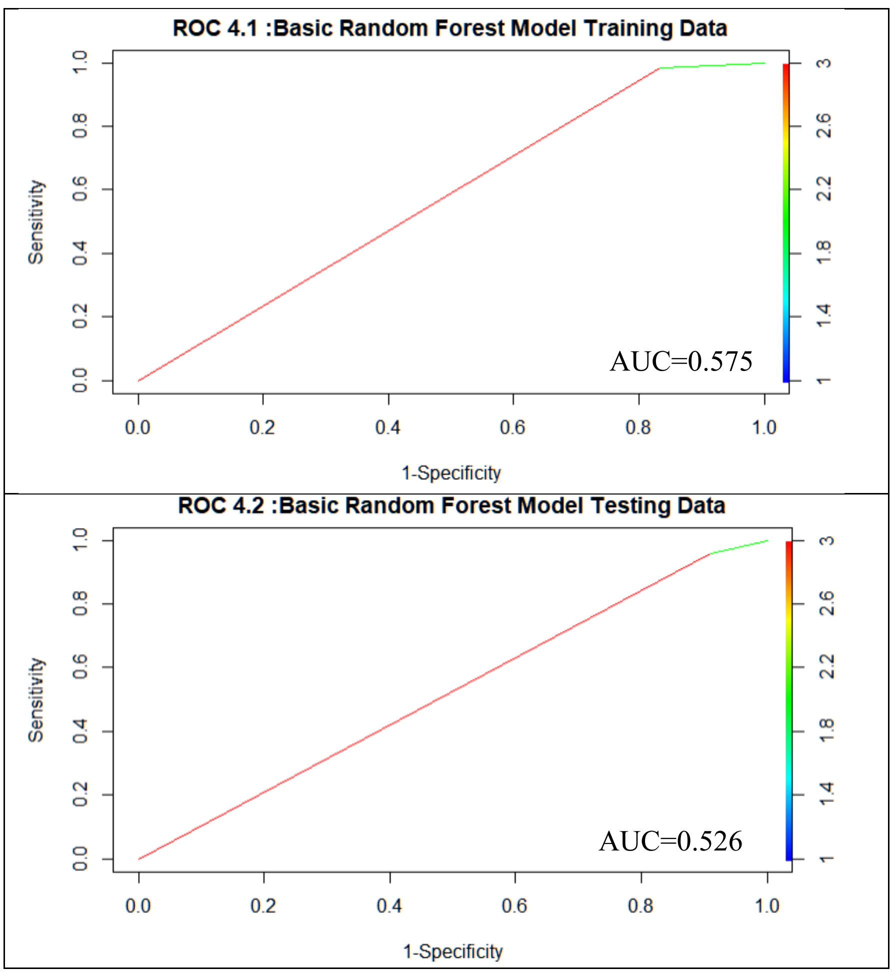

Figure 5.13: ROC curve for the basic Random Forest

Figure 5.14 shows the comparison of ROC curve for the optimized RF model in the training and testing data. The area under the ROC curve is computed and labeled in each diagram. It is observed that the training data area under ROC is 0.876 which is slightly higher than the testing data of 0.701. This indicates model has a good fit and provides acceptable performance in identifying the positive and negative class.

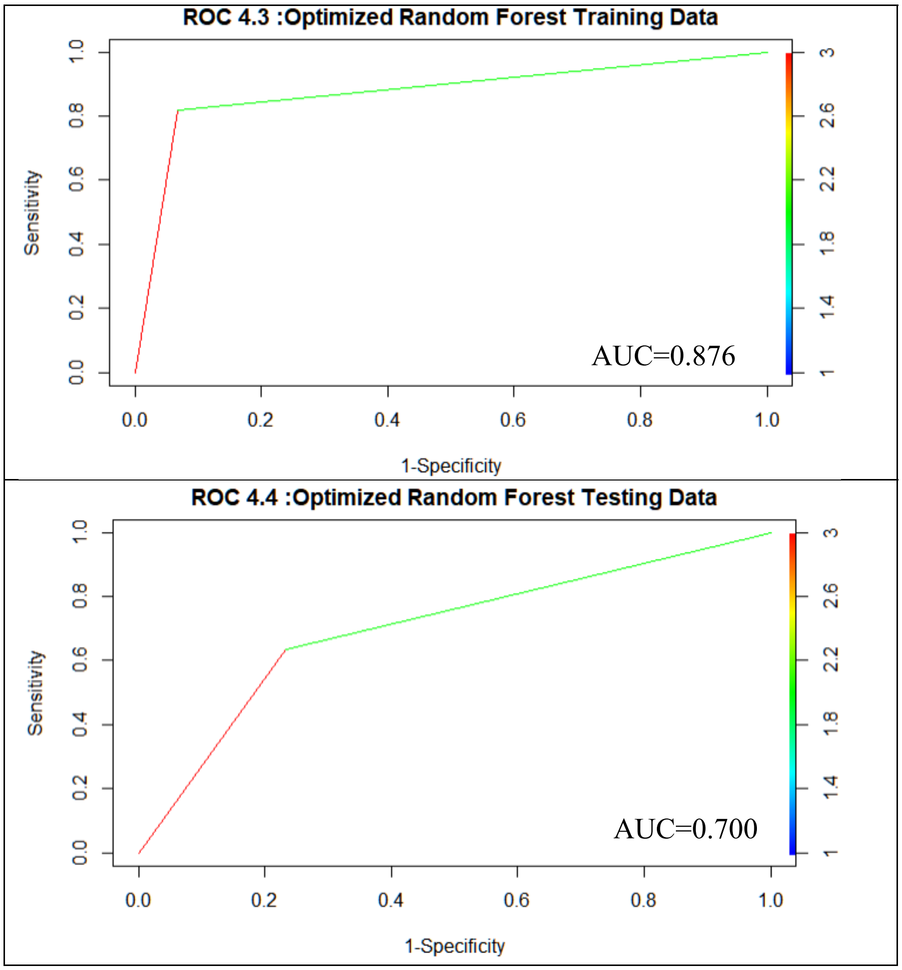

Figure 5.14: ROC curve for the optimized Random Forest

SECTION 6

ANALYSIS & RECOMMENDATIONS

6.1 RESULT ANALYSIS

Table 6.1: Evaluation results compilation of predictive models

Models	Hyperparameters & resampling		Accuracy	Kappa	Sensitivity	Specificity	AUROC
Logistic Regression	- Repeated 10-fold cv		0.6500	0.2772	0.5825	0.6960	0.6390
Basic XGBoost	- eta: 0.3	- colsample_bytree: 1	0.6745	0.3359	0.6510	0.6906	0.6710
	- gamma: 0	- min_child_weight: 1					
	- max_depth: 6	- nrounds: 100					
	- subsample: 1	- Repeated 10-fold cv					
Optimized XGBoost	- eta: 0.05	- colsample_bytree: 0.5	0.6832	0.3790	0.7924	0.6089	0.701
	- gamma: 0.6	- min_child_weight: 15					
	- max_depth: 5	- nrounds: 50					
	- subsample: 0.5	- Repeated 10-fold cv					
Basic AdaBoost	- mfinal: 50	- Repeated 10-fold cv	0.6491	0.3600	**0.9978**	0.4118	0.7050
	- maxdepth: 1						
Optimized AdaBoost	- mfinal: 200	- Repeated 10-fold cv	**0.6982**	**0.4298**	0.9349	**0.5371**	**0.7360**
	- maxdepth: 5						
Basic Random Forest	- mtry: 1		0.6082	0.0592	0.0909	0.9603	0.5260
Optimized Random Forest	- mtry: 2		0.6873	0.3813	0.7666	0.6333	0.7000
	- Repeated 10-fold CV						

Table 6.1 shows the compilation of all evaluation metric results for all the developed models in this study. In addition, the hyperparameters and resampling settings on each model is presented. Model with the best result in each evaluation metric is highlighted in bold as shown in the table. Based on Table 6.1, the following observations are identified and listed as followed:

- In terms of accuracy, optimized AdaBoost model obtained the highest accuracy of 69.82% which indicates the model provides good performance in ratio of correctly identifying the prediction as compared to the total observations.
- In terms of kappa, optimized AdaBoost model obtained the highest kappa of 0.4298 which indicates the model provides moderate agreement in the predictive performance.
- In terms of sensitivity, basic AdaBoost model obtained the highest sensitivity of 0.9978 which indicates the model provides a near perfect score at correctly classifying positive outcomes.
- In terms of specificity, optimized AdaBoost model obtained the highest specificity of 0.7360 which indicates the model provides a good score at correctly classifying negative outcomes.
- In terms of AUROC, optimized AdaBoost model obtained the highest area of 0.7360 which indicates the model is very likely to be able to distinguish between the positive and negative class.

In overall, the optimized AdaBoost model has obtained the highest score in four of the five evaluation metrics. Therefore, it can be concluded that the optimized AdaBoost model is the best performing model in this study.

6.2 RESULTS COMPARISON

This section discusses the comparison of results from this study to peers that have utilized the same dataset. Table 6.2 shows the compilation of results from literature using different models to predict the package delivery time. In addition, models from this study will be included in the table as a comparison in model performance.

Table 6.2: Model performance of peers from the same dataset

No.	Author	Prediction Model	Accuracy (%)
1	**From this study**	**AdaBoost**	**69.82**
2	**From this study**	**RF**	**68.73**
3	**From this study**	**XGBoost**	**68.32**
4	(Kumar, 2021)	ANN	67.00
5	(Kumar, 2021)	RF	66.00
6	(Kumar, 2021)	SVM	66.00
7	(Chandra, 2021)	RF	65.27
8	(Bagga, 2021)	KNN	65.00
9	(Bagga, 2021)	Logistic regression	65.00
10	(Chandra, 2021)	KNN	63.00

Based on Table 6.2, the best model performance from literature is by Kumar (2021) which uses ANN model and achieved an accuracy of 67%. However, all three prediction models from this study have outperformed the ANN model by at least 1.32% in terms of accuracy. This may be due to Kumar (2021) on not performing hyperparameter optimization on the ANN model. Although extensive hyperparameter optimization is performed on the models from this study, the model performance was just slightly better than the ANN model. Therefore, with proper hyperparameter tuning on the ANN model, better performance might be expected.

In specific comparison of the RF model result from this study to literature. It is observed that RF model from this study has outperformed the RF models from literature. In addition, it is observed that RF model was used by Kumar (2021) and Chandra (2021) which achieved an accuracy of 67% and 65.27% respectively. On further investigation into the works of Chandra (2021). The author did not perform any hyperparameter tuning on the model instead only relying on the basic RF model for the prediction. However, in the works of Kumar (2021), some hyperparameter tuning was performed on the number of trees parameter and the split quality criterion parameter. The parameter used in tuning the RF model in this study was the number of random sampling variables. This might indicate that the number of random sampling variables has a higher effect on the model performance.

SECTION 7

CONCLUSION

The increased package delivery frequency from the rapid expansion of e-commerce led to the generation of voluminous data which can be utilized to extract information such as predicting the delivery time of the packages. With the advancement of technologies, big data analytics has opened more doors to companies trying to gain value from all sorts of data available at hand. Which in this study, four machine learning algorithms are explored, and multiple prediction models are developed in trying to accurately predict the package delivery time. The algorithms involve are Logistic Regression, XGBoost, AdaBoost, and Random Forest. The best performing model is identified to be the optimized AdaBoost. In which, being able to accurately predict package delivery time enhances the operation efficiency and customer retention rate. The models in this study have outperformed the models from literature. However, the accuracy of the models can be further improved if larger dataset and features about weather condition can be incorporated in the prediction models. In addition, hyperparameter optimization can be further tuned to achieve even higher accuracy. Furthermore, ensembles of different algorithms can be explored to examine the effects of combining different models on the prediction accuracy.

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APPENDIX A

MODEL OPTIMIZATION RESULTS

AdaBoost Optimization Iterative Results

maxdepth	mfinal	Accuracy	Kappa
1	50	0.639617	0.344154
1	100	0.639617	0.344154
1	150	0.639617	0.344154
1	200	0.639617	0.344154
1	250	0.639617	0.344154
1	300	0.639617	0.344154
1	350	0.639617	0.344154
1	400	0.639617	0.344154
1	450	0.639617	0.344154
1	500	0.639617	0.344154
2	50	0.680415	0.360929
2	100	0.680302	0.360802
2	150	0.680302	0.360729
2	200	0.680264	0.360662
2	250	0.68034	0.360795
2	300	0.68034	0.360795
2	350	0.68034	0.360795
2	400	0.680377	0.360881
2	450	0.68034	0.360795
2	500	0.68034	0.360795
3	50	0.680453	0.361072
3	100	0.680188	0.360546
3	150	0.680264	0.360699
3	200	0.680226	0.360632
3	250	0.680188	0.360563
3	300	0.680074	0.360362
3	350	0.68015	0.360478
3	400	0.680302	0.360745
3	450	0.680226	0.360612
3	500	0.68034	0.360814

maxdepth	mfinal	Accuracy	Kappa
4	50	0.684737	0.404116
4	100	0.685343	0.405683
4	150	0.685608	0.406093
4	200	0.685949	0.406588
4	250	0.685797	0.40627
4	300	0.685646	0.406085
4	350	0.685077	0.405001
4	400	0.685494	0.405847
4	450	0.685456	0.405737
4	500	0.685343	0.405564
5	50	0.686251	0.40831
5	100	0.686214	0.408535
5	150	0.686479	0.409194
5	200	0.686554	0.409335
5	250	0.686516	0.409241
5	300	0.686327	0.40886
5	350	0.686441	0.409067
5	400	0.686327	0.408842
5	450	0.686175	0.408523
5	500	0.686138	0.408459
6	50	0.684773	0.402406
6	100	0.685758	0.404768
6	150	0.684736	0.402984
6	200	0.684812	0.403352
6	250	0.68466	0.403128
6	300	0.684357	0.402473
6	350	0.684584	0.403066
6	400	0.684281	0.402437
6	450	0.684281	0.402408
6	500	0.684281	0.402428

maxdepth	mfinal	Accuracy	Kappa
7	50	0.682159	0.393473
7	100	0.682653	0.395362
7	150	0.681137	0.393148
7	200	0.681894	0.394608
7	250	0.68216	0.395172
7	300	0.682917	0.396735
7	350	0.682576	0.396299
7	400	0.68269	0.396525
7	450	0.682614	0.396452
7	500	0.682235	0.395879
8	50	0.681324	0.390442
8	100	0.679924	0.38942
8	150	0.680113	0.389827
8	200	0.680341	0.390469
8	250	0.680758	0.391598
8	300	0.680758	0.391564
8	350	0.680303	0.39071
8	400	0.680266	0.390857
8	450	0.680379	0.390884
8	500	0.680531	0.391218
9	50	0.679206	0.385486
9	100	0.679054	0.386239
9	150	0.678901	0.386045
9	200	0.679129	0.38673
9	250	0.679128	0.386774
9	300	0.678977	0.386593
9	350	0.67928	0.3872
9	400	0.679015	0.386726
9	450	0.67875	0.386204
9	500	0.678939	0.386428
10	50	0.678674	0.382522
10	100	0.679812	0.385955
10	150	0.679205	0.385348
10	200	0.679129	0.385245
10	250	0.678825	0.384898
10	300	0.678825	0.385025
10	350	0.67856	0.384534
10	400	0.678749	0.384806
10	450	0.678711	0.38488
10	500	0.678976	0.385279

Random Forest Optimization Iterative Result

mtry	Accuracy	Kappa
1	0.600031	0.025266
2	0.676173	0.361281
3	0.671702	0.351499
4	0.666097	0.335035
5	0.665603	0.33257
6	0.663632	0.327403
7	0.663746	0.327098
8	0.663823	0.326875
9	0.662913	0.325542
10	0.663746	0.326856
11	0.663406	0.325998
12	0.662383	0.323208
13	0.663065	0.324945
14	0.662381	0.322834
15	0.662534	0.323317
16	0.66136	0.320838
17	0.662343	0.322937

XGBoost Optimization Iterative Result

#	eta	max_depth	gamma	colsample_bytree	min_child_weight	subsample	nrounds	Accuracy	Kappa
1	0.05	5	0	0.5	1	0.5	50	0.680796942	0.377960541
2	0.05	5	0	0.5	3	0.5	50	0.679850832	0.37722458
3	0.05	5	0	0.5	5	0.5	50	0.680039149	0.376219109
4	0.05	5	0	0.5	7	0.5	50	0.679700264	0.375265497
5	0.05	5	0	0.5	9	0.5	50	0.680418154	0.377799915
6	0.05	5	0	0.5	11	0.5	50	0.679662299	0.37538816
7	0.05	5	0	0.5	13	0.5	50	0.681516294	0.379582065
8	0.05	5	0	0.5	15	0.5	50	0.679168024	0.374565629
9	0.05	5	0	0.5	17	0.5	50	0.683032911	0.382168893
10	0.05	5	0	0.5	19	0.5	50	0.681592784	0.380822965
11	0.05	5	0.1	0.5	1	0.5	50	0.680342223	0.377561826
12	0.05	5	0.1	0.5	3	0.5	50	0.681251057	0.378382455
13	0.05	5	0.1	0.5	5	0.5	50	0.67833327	0.37259116
14	0.05	5	0.1	0.5	7	0.5	50	0.678031185	0.372923381
15	0.05	5	0.1	0.5	9	0.5	50	0.68041712	0.377251595
16	0.05	5	0.1	0.5	11	0.5	50	0.678446561	0.37302452
17	0.05	5	0.1	0.5	13	0.5	50	0.678977209	0.37507317
18	0.05	5	0.1	0.5	15	0.5	50	0.68071972	0.378448435
19	0.05	5	0.1	0.5	17	0.5	50	0.682349543	0.38071289
20	0.05	5	0.1	0.5	19	0.5	50	0.681819024	0.381325037
21	0.05	5	0.2	0.5	1	0.5	50	0.679017154	0.374296794
22	0.05	5	0.2	0.5	3	0.5	50	0.680949017	0.378342062
23	0.05	5	0.2	0.5	5	0.5	50	0.681023785	0.378786909
24	0.05	5	0.2	0.5	7	0.5	50	0.68117659	0.378842357
25	0.05	5	0.2	0.5	9	0.5	50	0.680381265	0.377485378
26	0.05	5	0.2	0.5	11	0.5	50	0.681290572	0.379439079
27	0.05	5	0.2	0.5	13	0.5	50	0.67924279	0.375530808
28	0.05	5	0.2	0.5	15	0.5	50	0.679660233	0.375899352
29	0.05	5	0.2	0.5	17	0.5	50	0.680458012	0.378361237
30	0.05	5	0.2	0.5	19	0.5	50	0.681404251	0.380350555
31	0.05	5	0.3	0.5	1	0.5	50	0.679434981	0.375442789
32	0.05	5	0.3	0.5	3	0.5	50	0.681440537	0.378512418
33	0.05	5	0.3	0.5	5	0.5	50	0.679889184	0.375801265
34	0.05	5	0.3	0.5	7	0.5	50	0.681554259	0.379858009
35	0.05	5	0.3	0.5	9	0.5	50	0.682350447	0.381232317
36	0.05	5	0.3	0.5	11	0.5	50	0.679700091	0.377004837
37	0.05	5	0.3	0.5	13	0.5	50	0.683070747	0.382895746
38	0.05	5	0.3	0.5	15	0.5	50	0.681365555	0.378795192
39	0.05	5	0.3	0.5	17	0.5	50	0.683070229	0.382596327
40	0.05	5	0.3	0.5	19	0.5	50	0.680456033	0.378563755
41	0.05	5	0.4	0.5	1	0.5	50	0.679963263	0.376801138
42	0.05	5	0.4	0.5	3	0.5	50	0.67954866	0.375030715
43	0.05	5	0.4	0.5	5	0.5	50	0.679774386	0.375284862
44	0.05	5	0.4	0.5	7	0.5	50	0.67844811	0.373024225
45	0.05	5	0.4	0.5	9	0.5	50	0.679470838	0.375385511
46	0.05	5	0.4	0.5	11	0.5	50	0.680415957	0.376332799
47	0.05	5	0.4	0.5	13	0.5	50	0.680380016	0.377320388
48	0.05	5	0.4	0.5	15	0.5	50	0.680002735	0.376465144
49	0.05	5	0.4	0.5	17	0.5	50	0.680949188	0.379269557
50	0.05	5	0.4	0.5	19	0.5	50	0.679926289	0.375838604
51	0.05	5	0.5	0.5	1	0.5	50	0.679849024	0.376029034
52	0.05	5	0.5	0.5	3	0.5	50	0.680759449	0.377877299
53	0.05	5	0.5	0.5	5	0.5	50	0.678600918	0.373785804
54	0.05	5	0.5	0.5	7	0.5	50	0.680078235	0.376369408
55	0.05	5	0.5	0.5	9	0.5	50	0.681706764	0.379063142
56	0.05	5	0.5	0.5	11	0.5	50	0.679621622	0.374595304
57	0.05	5	0.5	0.5	13	0.5	50	0.680607762	0.378206079
58	0.05	5	0.5	0.5	15	0.5	50	0.680910146	0.378169953
59	0.05	5	0.5	0.5	17	0.5	50	0.682918974	0.382263693
60	0.05	5	0.5	0.5	19	0.5	50	0.682500712	0.382214478
61	0.05	5	0.6	0.5	1	0.5	50	0.68276737	0.380066293
62	0.05	5	0.6	0.5	3	0.5	50	0.680001788	0.376785004
63	0.05	5	0.6	0.5	5	0.5	50	0.677803784	0.372053869
64	0.05	5	0.6	0.5	7	0.5	50	0.679169142	0.374541809
65	0.05	5	0.6	0.5	9	0.5	50	0.680644825	0.377044445
66	0.05	5	0.6	0.5	11	0.5	50	0.679925255	0.376450847
67	0.05	5	0.6	0.5	13	0.5	50	0.679812136	0.376686751
68	0.05	5	0.6	0.5	15	0.5	50	0.683751489	0.384504886
69	0.05	5	0.6	0.5	17	0.5	50	0.680683521	0.378228222
70	0.05	5	0.6	0.5	19	0.5	50	0.680154638	0.37666347
71	0.05	5	0.7	0.5	1	0.5	50	0.679964556	0.375018348
72	0.05	5	0.7	0.5	3	0.5	50	0.679243437	0.374875908
73	0.05	5	0.7	0.5	5	0.5	50	0.680989005	0.378853933
74	0.05	5	0.7	0.5	7	0.5	50	0.679394737	0.375526612
75	0.05	5	0.7	0.5	9	0.5	50	0.678938814	0.374739178
76	0.05	5	0.7	0.5	11	0.5	50	0.677841879	0.37247225
77	0.05	5	0.7	0.5	13	0.5	50	0.682538893	0.381797049
78	0.05	5	0.7	0.5	15	0.5	50	0.683032653	0.384312411
79	0.05	5	0.7	0.5	17	0.5	50	0.68265421	0.382363992
80	0.05	5	0.7	0.5	19	0.5	50	0.681896289	0.380136438
81	0.05	5	0.8	0.5	1	0.5	50	0.682161354	0.381738871
82	0.05	5	0.8	0.5	3	0.5	50	0.679358192	0.375072677
83	0.05	5	0.8	0.5	5	0.5	50	0.680190535	0.376428156
84	0.05	5	0.8	0.5	7	0.5	50	0.678373128	0.372937609
85	0.05	5	0.8	0.5	9	0.5	50	0.680380361	0.376897399
86	0.05	5	0.8	0.5	11	0.5	50	0.680683134	0.377646154
87	0.05	5	0.8	0.5	13	0.5	50	0.682084864	0.38080683
88	0.05	5	0.8	0.5	15	0.5	50	0.680154164	0.377961191
89	0.05	5	0.8	0.5	17	0.5	50	0.682614867	0.381223537
90	0.05	5	0.8	0.5	19	0.5	50	0.681743395	0.379688156
91	0.05	5	0.9	0.5	1	0.5	50	0.679434551	0.375320711
92	0.05	5	0.9	0.5	3	0.5	50	0.68003928	0.377185891
93	0.05	5	0.9	0.5	5	0.5	50	0.679168025	0.374596371
94	0.05	5	0.9	0.5	7	0.5	50	0.68181954	0.381135888
95	0.05	5	0.9	0.5	9	0.5	50	0.681781617	0.380093183
96	0.05	5	0.9	0.5	11	0.5	50	0.680493739	0.377982853
97	0.05	5	0.9	0.5	13	0.5	50	0.680909587	0.378314981
98	0.05	5	0.9	0.5	15	0.5	50	0.678561834	0.372517179
99	0.05	5	0.9	0.5	17	0.5	50	0.683372873	0.383600981
100	0.05	5	0.9	0.5	19	0.5	50	0.680114435	0.378305239
101	0.05	5	1	0.5	1	0.5	50	0.681707498	0.380207556
102	0.05	5	1	0.5	3	0.5	50	0.680230309	0.376264312
103	0.05	5	1	0.5	5	0.5	50	0.68022919	0.377136857
104	0.05	5	1	0.5	7	0.5	50	0.681781619	0.379877325
105	0.05	5	1	0.5	9	0.5	50	0.680267369	0.377441421
106	0.05	5	1	0.5	11	0.5	50	0.679168971	0.374265571
107	0.05	5	1	0.5	13	0.5	50	0.680419058	0.375950628
108	0.05	5	1	0.5	15	0.5	50	0.68159313	0.379367206
109	0.05	5	1	0.5	17	0.5	50	0.680075952	0.377245242
110	0.05	5	1	0.5	19	0.5	50	0.682121968	0.38077108
111	0.05	6	0	0.5	1	0.5	50	0.679357849	0.372180831
112	0.05	6	0	0.5	3	0.5	50	0.67886314	0.370446383
113	0.05	6	0	0.5	5	0.5	50	0.67772811	0.369841368
114	0.05	6	0	0.5	7	0.5	50	0.678486807	0.370481719
115	0.05	6	0	0.5	9	0.5	50	0.678408767	0.370101475
116	0.05	6	0	0.5	11	0.5	50	0.680000367	0.374104113
117	0.05	6	0	0.5	13	0.5	50	0.675153515	0.363981522
118	0.05	6	0	0.5	15	0.5	50	0.679773696	0.373611159
119	0.05	6	0	0.5	17	0.5	50	0.67780486	0.369893747
120	0.05	6	0	0.5	19	0.5	50	0.679206849	0.373097963
121	0.05	6	0.1	0.5	1	0.5	50	0.678334131	0.36921612
122	0.05	6	0.1	0.5	3	0.5	50	0.678978154	0.370151921
123	0.05	6	0.1	0.5	5	0.5	50	0.678143701	0.369812021
124	0.05	6	0.1	0.5	7	0.5	50	0.675834645	0.365938964
125	0.05	6	0.1	0.5	9	0.5	50	0.675833784	0.364838336
126	0.05	6	0.1	0.5	11	0.5	50	0.678336798	0.369909886
127	0.05	6	0.1	0.5	13	0.5	50	0.680040011	0.374590942
128	0.05	6	0.1	0.5	15	0.5	50	0.679433217	0.372621062
129	0.05	6	0.1	0.5	17	0.5	50	0.680228459	0.375193728
130	0.05	6	0.1	0.5	19	0.5	50	0.678676287	0.372436299
131	0.05	6	0.2	0.5	1	0.5	50	0.675797194	0.363972723
132	0.05	6	0.2	0.5	3	0.5	50	0.675342908	0.363842872
133	0.05	6	0.2	0.5	5	0.5	50	0.679582366	0.372966498
134	0.05	6	0.2	0.5	7	0.5	50	0.678448842	0.370183756
135	0.05	6	0.2	0.5	9	0.5	50	0.678598592	0.370600412
136	0.05	6	0.2	0.5	11	0.5	50	0.680268574	0.373333456
137	0.05	6	0.2	0.5	13	0.5	50	0.67799348	0.36936846
138	0.05	6	0.2	0.5	15	0.5	50	0.677465069	0.368116751
139	0.05	6	0.2	0.5	17	0.5	50	0.677917978	0.369955967
140	0.05	6	0.2	0.5	19	0.5	50	0.68185587	0.37836318
141	0.05	6	0.3	0.5	1	0.5	50	0.676363741	0.364412526
142	0.05	6	0.3	0.5	3	0.5	50	0.676552662	0.366097908
143	0.05	6	0.3	0.5	5	0.5	50	0.679774686	0.372727584
144	0.05	6	0.3	0.5	7	0.5	50	0.676439714	0.367422852
145	0.05	6	0.3	0.5	9	0.5	50	0.676477852	0.366099264
146	0.05	6	0.3	0.5	11	0.5	50	0.679281919	0.371653761
147	0.05	6	0.3	0.5	13	0.5	50	0.677651753	0.368912838
148	0.05	6	0.3	0.5	15	0.5	50	0.678070356	0.369541354
149	0.05	6	0.3	0.5	17	0.5	50	0.680795696	0.375222404
150	0.05	6	0.3	0.5	19	0.5	50	0.682311105	0.379025555

#	eta	max_depth	gamma	colsample_bytree	min_child_weight	subsample	nrounds	Accuracy	Kappa
151	0.05	6	0.4	0.5	1	0.5	50	0.676629798	0.365605571
152	0.05	6	0.4	0.5	3	0.5	50	0.675795474	0.364325499
153	0.05	6	0.4	0.5	5	0.5	50	0.677881822	0.368320447
154	0.05	6	0.4	0.5	7	0.5	50	0.676932744	0.366829956
155	0.05	6	0.4	0.5	9	0.5	50	0.677918625	0.369600607
156	0.05	6	0.4	0.5	11	0.5	50	0.680378768	0.37419944
157	0.05	6	0.4	0.5	13	0.5	50	0.67708387	0.368122989
158	0.05	6	0.4	0.5	15	0.5	50	0.679698026	0.372988992
159	0.05	6	0.4	0.5	17	0.5	50	0.679395812	0.37335051
160	0.05	6	0.4	0.5	19	0.5	50	0.680114951	0.374790873
161	0.05	6	0.5	0.5	1	0.5	50	0.678977553	0.371085382
162	0.05	6	0.5	0.5	3	0.5	50	0.679771974	0.37294761
163	0.05	6	0.5	0.5	5	0.5	50	0.675949097	0.363007424
164	0.05	6	0.5	0.5	7	0.5	50	0.677727208	0.368975554
165	0.05	6	0.5	0.5	9	0.5	50	0.67947058	0.372545328
166	0.05	6	0.5	0.5	11	0.5	50	0.67947269	0.373595578
167	0.05	6	0.5	0.5	13	0.5	50	0.679164967	0.370216298
168	0.05	6	0.5	0.5	15	0.5	50	0.678256607	0.3705216
169	0.05	6	0.5	0.5	17	0.5	50	0.680530756	0.37505712
170	0.05	6	0.5	0.5	19	0.5	50	0.679394693	0.373338916
171	0.05	6	0.6	0.5	1	0.5	50	0.678789622	0.370200532
172	0.05	6	0.6	0.5	3	0.5	50	0.677085119	0.367434807
173	0.05	6	0.6	0.5	5	0.5	50	0.677804169	0.367592982
174	0.05	6	0.6	0.5	7	0.5	50	0.677916516	0.370196045
175	0.05	6	0.6	0.5	9	0.5	50	0.676477896	0.367157538
176	0.05	6	0.6	0.5	11	0.5	50	0.678141938	0.368915436
177	0.05	6	0.6	0.5	13	0.5	50	0.678977682	0.370743808
178	0.05	6	0.6	0.5	15	0.5	50	0.679280196	0.372634896
179	0.05	6	0.6	0.5	17	0.5	50	0.680683606	0.375890836
180	0.05	6	0.6	0.5	19	0.5	50	0.68140283	0.377161648
181	0.05	6	0.7	0.5	1	0.5	50	0.674962009	0.363125265
182	0.05	6	0.7	0.5	3	0.5	50	0.679739262	0.372775128
183	0.05	6	0.7	0.5	5	0.5	50	0.679094418	0.372001673
184	0.05	6	0.7	0.5	7	0.5	50	0.675529591	0.363090369
185	0.05	6	0.7	0.5	9	0.5	50	0.678181409	0.368863699
186	0.05	6	0.7	0.5	11	0.5	50	0.678597948	0.369665486
187	0.05	6	0.7	0.5	13	0.5	50	0.678486849	0.370750084
188	0.05	6	0.7	0.5	15	0.5	50	0.679129155	0.372171295
189	0.05	6	0.7	0.5	17	0.5	50	0.679584518	0.373364515
190	0.05	6	0.7	0.5	19	0.5	50	0.679850489	0.374265836
191	0.05	6	0.8	0.5	1	0.5	50	0.674621962	0.361572978
192	0.05	6	0.8	0.5	3	0.5	50	0.676630703	0.365067072
193	0.05	6	0.8	0.5	5	0.5	50	0.67651754	0.364762693
194	0.05	6	0.8	0.5	7	0.5	50	0.678106813	0.368931579
195	0.05	6	0.8	0.5	9	0.5	50	0.677767369	0.369241376
196	0.05	6	0.8	0.5	11	0.5	50	0.680415097	0.373702293
197	0.05	6	0.8	0.5	13	0.5	50	0.677840671	0.369300313
198	0.05	6	0.8	0.5	15	0.5	50	0.679774817	0.373317331
199	0.05	6	0.8	0.5	17	0.5	50	0.680114822	0.37467063
200	0.05	6	0.8	0.5	19	0.5	50	0.680909932	0.375955225
201	0.05	6	0.9	0.5	1	0.5	50	0.677009491	0.365719947
202	0.05	6	0.9	0.5	3	0.5	50	0.676213733	0.364211117
203	0.05	6	0.9	0.5	5	0.5	50	0.677916387	0.368946433
204	0.05	6	0.9	0.5	7	0.5	50	0.677159283	0.367514005
205	0.05	6	0.9	0.5	9	0.5	50	0.674773564	0.361999816
206	0.05	6	0.9	0.5	11	0.5	50	0.677121405	0.368247296
207	0.05	6	0.9	0.5	13	0.5	50	0.678335421	0.371378712
208	0.05	6	0.9	0.5	15	0.5	50	0.681442086	0.376334071
209	0.05	6	0.9	0.5	17	0.5	50	0.67708387	0.368113185
210	0.05	6	0.9	0.5	19	0.5	50	0.679584131	0.374312971
211	0.05	6	1	0.5	1	0.5	50	0.677691179	0.368418995
212	0.05	6	1	0.5	3	0.5	50	0.679660922	0.371856321
213	0.05	6	1	0.5	5	0.5	50	0.677917549	0.368959515
214	0.05	6	1	0.5	7	0.5	50	0.677007854	0.366765292
215	0.05	6	1	0.5	9	0.5	50	0.677878077	0.369419221
216	0.05	6	1	0.5	11	0.5	50	0.679583958	0.373508171
217	0.05	6	1	0.5	13	0.5	50	0.680456376	0.375292716
218	0.05	6	1	0.5	15	0.5	50	0.679052278	0.371559762
219	0.05	6	1	0.5	17	0.5	50	0.678750797	0.371856243
220	0.05	6	1	0.5	19	0.5	50	0.678828019	0.372940429
221	0.05	7	0	0.5	1	0.5	50	0.672881389	0.354138198
222	0.05	7	0	0.5	3	0.5	50	0.672842863	0.35624848
223	0.05	7	0	0.5	5	0.5	50	0.676062433	0.36226531
224	0.05	7	0	0.5	7	0.5	50	0.672917115	0.356456705
225	0.05	7	0	0.5	9	0.5	50	0.673142837	0.357329739
226	0.05	7	0	0.5	11	0.5	50	0.674243604	0.360236641
227	0.05	7	0	0.5	13	0.5	50	0.676060755	0.363234189
228	0.05	7	0	0.5	15	0.5	50	0.675606769	0.361937658
229	0.05	7	0	0.5	17	0.5	50	0.678790956	0.369838629
230	0.05	7	0	0.5	19	0.5	50	0.678638193	0.369153033
231	0.05	7	0.1	0.5	1	0.5	50	0.674622737	0.357887954
232	0.05	7	0.1	0.5	3	0.5	50	0.675646583	0.361156819
233	0.05	7	0.1	0.5	5	0.5	50	0.676666901	0.363527368
234	0.05	7	0.1	0.5	7	0.5	50	0.676288714	0.362549291
235	0.05	7	0.1	0.5	9	0.5	50	0.672009529	0.353452317
236	0.05	7	0.1	0.5	11	0.5	50	0.673374371	0.356317028
237	0.05	7	0.1	0.5	13	0.5	50	0.677767496	0.367235397
238	0.05	7	0.1	0.5	15	0.5	50	0.677653818	0.366532056
239	0.05	7	0.1	0.5	17	0.5	50	0.67935901	0.370905884
240	0.05	7	0.1	0.5	19	0.5	50	0.678791173	0.369326252
241	0.05	7	0.2	0.5	1	0.5	50	0.675305846	0.359319826
242	0.05	7	0.2	0.5	3	0.5	50	0.675721869	0.361482373
243	0.05	7	0.2	0.5	5	0.5	50	0.674586794	0.358461203
244	0.05	7	0.2	0.5	7	0.5	50	0.677956158	0.366822203
245	0.05	7	0.2	0.5	9	0.5	50	0.674203745	0.359836639
246	0.05	7	0.2	0.5	11	0.5	50	0.675152267	0.361281617
247	0.05	7	0.2	0.5	13	0.5	50	0.675607197	0.362559619
248	0.05	7	0.2	0.5	15	0.5	50	0.676325432	0.363272717
249	0.05	7	0.2	0.5	17	0.5	50	0.676667505	0.365117188
250	0.05	7	0.2	0.5	19	0.5	50	0.679164494	0.370703299
251	0.05	7	0.3	0.5	1	0.5	50	0.676629626	0.362207098
252	0.05	7	0.3	0.5	3	0.5	50	0.674016933	0.356835676
253	0.05	7	0.3	0.5	5	0.5	50	0.676215626	0.362480765
254	0.05	7	0.3	0.5	7	0.5	50	0.673333911	0.357248627
255	0.05	7	0.3	0.5	9	0.5	50	0.675757423	0.362280601
256	0.05	7	0.3	0.5	11	0.5	50	0.67518881	0.361180454
257	0.05	7	0.3	0.5	13	0.5	50	0.677084731	0.367038941
258	0.05	7	0.3	0.5	15	0.5	50	0.675076379	0.36199754
259	0.05	7	0.3	0.5	17	0.5	50	0.679205084	0.371746104
260	0.05	7	0.3	0.5	19	0.5	50	0.678939716	0.371095944
261	0.05	7	0.4	0.5	1	0.5	50	0.676592566	0.362614313
262	0.05	7	0.4	0.5	3	0.5	50	0.673601473	0.356689055
263	0.05	7	0.4	0.5	5	0.5	50	0.675342865	0.36038157
264	0.05	7	0.4	0.5	7	0.5	50	0.676290438	0.362954411
265	0.05	7	0.4	0.5	9	0.5	50	0.67640162	0.363072795
266	0.05	7	0.4	0.5	11	0.5	50	0.675038887	0.362244175
267	0.05	7	0.4	0.5	13	0.5	50	0.678259018	0.368103545
268	0.05	7	0.4	0.5	15	0.5	50	0.67954694	0.371385472
269	0.05	7	0.4	0.5	17	0.5	50	0.675531959	0.363256144
270	0.05	7	0.4	0.5	19	0.5	50	0.677803654	0.369136836
271	0.05	7	0.5	0.5	1	0.5	50	0.674017322	0.355827703
272	0.05	7	0.5	0.5	3	0.5	50	0.675002343	0.358378506
273	0.05	7	0.5	0.5	5	0.5	50	0.67666914	0.362368149
274	0.05	7	0.5	0.5	7	0.5	50	0.67571828	0.361780081
275	0.05	7	0.5	0.5	9	0.5	50	0.674662768	0.361207807
276	0.05	7	0.5	0.5	11	0.5	50	0.67492495	0.361093219
277	0.05	7	0.5	0.5	13	0.5	50	0.675645422	0.363389285
278	0.05	7	0.5	0.5	15	0.5	50	0.676063294	0.363605965
279	0.05	7	0.5	0.5	17	0.5	50	0.679962488	0.372506355
280	0.05	7	0.5	0.5	19	0.5	50	0.677083399	0.367040596
281	0.05	7	0.6	0.5	1	0.5	50	0.672121745	0.353035618
282	0.05	7	0.6	0.5	3	0.5	50	0.674469843	0.357695496
283	0.05	7	0.6	0.5	5	0.5	50	0.671554812	0.352518596
284	0.05	7	0.6	0.5	7	0.5	50	0.674129752	0.357665759
285	0.05	7	0.6	0.5	9	0.5	50	0.673751352	0.357217206
286	0.05	7	0.6	0.5	11	0.5	50	0.677651148	0.366973767
287	0.05	7	0.6	0.5	13	0.5	50	0.678220192	0.366743515
288	0.05	7	0.6	0.5	15	0.5	50	0.678676761	0.368952986
289	0.05	7	0.6	0.5	17	0.5	50	0.679698414	0.371800341
290	0.05	7	0.6	0.5	19	0.5	50	0.677386773	0.367678264
291	0.05	7	0.7	0.5	1	0.5	50	0.672084598	0.351901977
292	0.05	7	0.7	0.5	3	0.5	50	0.676895767	0.36235233
293	0.05	7	0.7	0.5	5	0.5	50	0.673675895	0.357574153
294	0.05	7	0.7	0.5	7	0.5	50	0.676556064	0.362862808
295	0.05	7	0.7	0.5	9	0.5	50	0.67666716	0.364583691
296	0.05	7	0.7	0.5	11	0.5	50	0.6757981	0.363090076
297	0.05	7	0.7	0.5	13	0.5	50	0.674813464	0.360533165
298	0.05	7	0.7	0.5	15	0.5	50	0.678484611	0.369542366
299	0.05	7	0.7	0.5	17	0.5	50	0.675720965	0.363719829
300	0.05	7	0.7	0.5	19	0.5	50	0.680000539	0.372786281

#	eta	max_depth	gamma	colsample_bytree	min_child_weight	subsample	nrounds	Accuracy	Kappa
301	0.05	7	0.8	0.5	1	0.5	50	0.676478627	0.361237455
302	0.05	7	0.8	0.5	3	0.5	50	0.67420749	0.356041275
303	0.05	7	0.8	0.5	5	0.5	50	0.674659926	0.359071908
304	0.05	7	0.8	0.5	7	0.5	50	0.673144345	0.35610908
305	0.05	7	0.8	0.5	9	0.5	50	0.675153213	0.360786367
306	0.05	7	0.8	0.5	11	0.5	50	0.676251613	0.36331749
307	0.05	7	0.8	0.5	13	0.5	50	0.676441481	0.364478956
308	0.05	7	0.8	0.5	15	0.5	50	0.678485087	0.368537382
309	0.05	7	0.8	0.5	17	0.5	50	0.677236764	0.367470335
310	0.05	7	0.8	0.5	19	0.5	50	0.677802406	0.368635169
311	0.05	7	0.9	0.5	1	0.5	50	0.673071645	0.354253058
312	0.05	7	0.9	0.5	3	0.5	50	0.675570826	0.360595418
313	0.05	7	0.9	0.5	5	0.5	50	0.672727245	0.355237905
314	0.05	7	0.9	0.5	7	0.5	50	0.676250838	0.361957647
315	0.05	7	0.9	0.5	9	0.5	50	0.677046334	0.364996437
316	0.05	7	0.9	0.5	11	0.5	50	0.678109483	0.36690664
317	0.05	7	0.9	0.5	13	0.5	50	0.67893963	0.369463556
318	0.05	7	0.9	0.5	15	0.5	50	0.681175085	0.373818466
319	0.05	7	0.9	0.5	17	0.5	50	0.675001267	0.362670391
320	0.05	7	0.9	0.5	19	0.5	50	0.679207065	0.37180209
321	0.05	7	1	0.5	1	0.5	50	0.673106379	0.354498749
322	0.05	7	1	0.5	3	0.5	50	0.672993303	0.354761923
323	0.05	7	1	0.5	5	0.5	50	0.676516807	0.364115086
324	0.05	7	1	0.5	7	0.5	50	0.673750317	0.3574429
325	0.05	7	1	0.5	9	0.5	50	0.67765175	0.366035633
326	0.05	7	1	0.5	11	0.5	50	0.679660621	0.371167687
327	0.05	7	1	0.5	13	0.5	50	0.675301757	0.360774695
328	0.05	7	1	0.5	15	0.5	50	0.676439285	0.364674937
329	0.05	7	1	0.5	17	0.5	50	0.678031359	0.368398003
330	0.05	7	1	0.5	19	0.5	50	0.677616111	0.368793126
331	0.05	8	0	0.5	1	0.5	50	0.670040648	0.344434112
332	0.05	8	0	0.5	3	0.5	50	0.671213168	0.347687855
333	0.05	8	0	0.5	5	0.5	50	0.671552443	0.349703012
334	0.05	8	0	0.5	7	0.5	50	0.673597943	0.353855523
335	0.05	8	0	0.5	9	0.5	50	0.674548872	0.357189492
336	0.05	8	0	0.5	11	0.5	50	0.675267408	0.360165439
337	0.05	8	0	0.5	13	0.5	50	0.676289406	0.361890154
338	0.05	8	0	0.5	15	0.5	50	0.674657561	0.359448078
339	0.05	8	0	0.5	17	0.5	50	0.675609653	0.361134428
340	0.05	8	0	0.5	19	0.5	50	0.676933347	0.365477295
341	0.05	8	0.1	0.5	1	0.5	50	0.668867222	0.343206224
342	0.05	8	0.1	0.5	3	0.5	50	0.671744075	0.350035402
343	0.05	8	0.1	0.5	5	0.5	50	0.670947975	0.348157575
344	0.05	8	0.1	0.5	7	0.5	50	0.673676023	0.35331816
345	0.05	8	0.1	0.5	9	0.5	50	0.672765212	0.353419368
346	0.05	8	0.1	0.5	11	0.5	50	0.672424303	0.353121118
347	0.05	8	0.1	0.5	13	0.5	50	0.672616109	0.355512515
348	0.05	8	0.1	0.5	15	0.5	50	0.676364603	0.362927322
349	0.05	8	0.1	0.5	17	0.5	50	0.676101474	0.361508344
350	0.05	8	0.1	0.5	19	0.5	50	0.675530796	0.361724166
351	0.05	8	0.2	0.5	1	0.5	50	0.669207315	0.344092102
352	0.05	8	0.2	0.5	3	0.5	50	0.672237921	0.349872817
353	0.05	8	0.2	0.5	5	0.5	50	0.672049474	0.349670944
354	0.05	8	0.2	0.5	7	0.5	50	0.670645332	0.34863489
355	0.05	8	0.2	0.5	9	0.5	50	0.673638705	0.355210298
356	0.05	8	0.2	0.5	11	0.5	50	0.675341788	0.359195736
357	0.05	8	0.2	0.5	13	0.5	50	0.674393873	0.358106479
358	0.05	8	0.2	0.5	15	0.5	50	0.67655529	0.363407121
359	0.05	8	0.2	0.5	17	0.5	50	0.676782862	0.363544756
360	0.05	8	0.2	0.5	19	0.5	50	0.677273695	0.365569615
361	0.05	8	0.3	0.5	1	0.5	50	0.669770716	0.344522806
362	0.05	8	0.3	0.5	3	0.5	50	0.670645673	0.346319832
363	0.05	8	0.3	0.5	5	0.5	50	0.672122519	0.350206344
364	0.05	8	0.3	0.5	7	0.5	50	0.67265377	0.353928488
365	0.05	8	0.3	0.5	9	0.5	50	0.675228927	0.359796102
366	0.05	8	0.3	0.5	11	0.5	50	0.67662898	0.36319128
367	0.05	8	0.3	0.5	13	0.5	50	0.674396022	0.358783503
368	0.05	8	0.3	0.5	15	0.5	50	0.675304212	0.361416873
369	0.05	8	0.3	0.5	17	0.5	50	0.675455296	0.362636782
370	0.05	8	0.3	0.5	19	0.5	50	0.675419269	0.361938289
371	0.05	8	0.4	0.5	1	0.5	50	0.671553605	0.348343848
372	0.05	8	0.4	0.5	3	0.5	50	0.671783504	0.349877607
373	0.05	8	0.4	0.5	5	0.5	50	0.675076593	0.356179396
374	0.05	8	0.4	0.5	7	0.5	50	0.67030253	0.34786193
375	0.05	8	0.4	0.5	9	0.5	50	0.672766761	0.353142467
376	0.05	8	0.4	0.5	11	0.5	50	0.676365852	0.361631188
377	0.05	8	0.4	0.5	13	0.5	50	0.67772979	0.364599363
378	0.05	8	0.4	0.5	15	0.5	50	0.675532172	0.361646556
379	0.05	8	0.4	0.5	17	0.5	50	0.675606123	0.361240161
380	0.05	8	0.4	0.5	19	0.5	50	0.677388667	0.36593449
381	0.05	8	0.5	0.5	1	0.5	50	0.673183385	0.352838379
382	0.05	8	0.5	0.5	3	0.5	50	0.670416812	0.346067548
383	0.05	8	0.5	0.5	5	0.5	50	0.669775367	0.345349674
384	0.05	8	0.5	0.5	7	0.5	50	0.673450948	0.353948957
385	0.05	8	0.5	0.5	9	0.5	50	0.672237577	0.352397007
386	0.05	8	0.5	0.5	11	0.5	50	0.673485124	0.355275822
387	0.05	8	0.5	0.5	13	0.5	50	0.675192298	0.360430695
388	0.05	8	0.5	0.5	15	0.5	50	0.676704176	0.363803632
389	0.05	8	0.5	0.5	17	0.5	50	0.675493607	0.361426773
390	0.05	8	0.5	0.5	19	0.5	50	0.677272532	0.365714645
391	0.05	8	0.6	0.5	1	0.5	50	0.669510389	0.343485055
392	0.05	8	0.6	0.5	3	0.5	50	0.674090969	0.354256141
393	0.05	8	0.6	0.5	5	0.5	50	0.673711192	0.35453979
394	0.05	8	0.6	0.5	7	0.5	50	0.669888315	0.347383879
395	0.05	8	0.6	0.5	9	0.5	50	0.675383628	0.358426851
396	0.05	8	0.6	0.5	11	0.5	50	0.676441565	0.362752591
397	0.05	8	0.6	0.5	13	0.5	50	0.674129667	0.357050589
398	0.05	8	0.6	0.5	15	0.5	50	0.675380357	0.360877105
399	0.05	8	0.6	0.5	17	0.5	50	0.673525027	0.356455044
400	0.05	8	0.6	0.5	19	0.5	50	0.675303395	0.362301803
401	0.05	8	0.7	0.5	1	0.5	50	0.66935659	0.343989956
402	0.05	8	0.7	0.5	3	0.5	50	0.671513963	0.348692136
403	0.05	8	0.7	0.5	5	0.5	50	0.672425249	0.350489763
404	0.05	8	0.7	0.5	7	0.5	50	0.673221179	0.354744827
405	0.05	8	0.7	0.5	9	0.5	50	0.671895331	0.352366072
406	0.05	8	0.7	0.5	11	0.5	50	0.671970574	0.352787938
407	0.05	8	0.7	0.5	13	0.5	50	0.673297022	0.357084942
408	0.05	8	0.7	0.5	15	0.5	50	0.676060282	0.362663954
409	0.05	8	0.7	0.5	17	0.5	50	0.676819622	0.36399319
410	0.05	8	0.7	0.5	19	0.5	50	0.67901668	0.370501011
411	0.05	8	0.8	0.5	1	0.5	50	0.671101081	0.348035226
412	0.05	8	0.8	0.5	3	0.5	50	0.672728925	0.351713506
413	0.05	8	0.8	0.5	5	0.5	50	0.671555156	0.349553528
414	0.05	8	0.8	0.5	7	0.5	50	0.673979529	0.355663752
415	0.05	8	0.8	0.5	9	0.5	50	0.673371917	0.353900804
416	0.05	8	0.8	0.5	11	0.5	50	0.674774167	0.358291093
417	0.05	8	0.8	0.5	13	0.5	50	0.674054513	0.357404567
418	0.05	8	0.8	0.5	15	0.5	50	0.67704638	0.36500406
419	0.05	8	0.8	0.5	17	0.5	50	0.676214122	0.363602895
420	0.05	8	0.8	0.5	19	0.5	50	0.675265428	0.36236381
421	0.05	8	0.9	0.5	1	0.5	50	0.667692852	0.340342628
422	0.05	8	0.9	0.5	3	0.5	50	0.671628889	0.350333236
423	0.05	8	0.9	0.5	5	0.5	50	0.671517146	0.348977907
424	0.05	8	0.9	0.5	7	0.5	50	0.673939843	0.35579351
425	0.05	8	0.9	0.5	9	0.5	50	0.672992355	0.354682662
426	0.05	8	0.9	0.5	11	0.5	50	0.672538196	0.354381846
427	0.05	8	0.9	0.5	13	0.5	50	0.673258239	0.354903868
428	0.05	8	0.9	0.5	15	0.5	50	0.675076811	0.361176455
429	0.05	8	0.9	0.5	17	0.5	50	0.676063382	0.36387865
430	0.05	8	0.9	0.5	19	0.5	50	0.676668667	0.364421719
431	0.05	8	1	0.5	1	0.5	50	0.674586753	0.354721944
432	0.05	8	1	0.5	3	0.5	50	0.670911602	0.347070661
433	0.05	8	1	0.5	5	0.5	50	0.672387629	0.350997667
434	0.05	8	1	0.5	7	0.5	50	0.674432914	0.356463485
435	0.05	8	1	0.5	9	0.5	50	0.673980262	0.356541632
436	0.05	8	1	0.5	11	0.5	50	0.673673657	0.357141049
437	0.05	8	1	0.5	13	0.5	50	0.674054427	0.357679812
438	0.05	8	1	0.5	15	0.5	50	0.673333652	0.356368584
439	0.05	8	1	0.5	17	0.5	50	0.676326981	0.364321789
440	0.05	8	1	0.5	19	0.5	50	0.679736679	0.370950105
441	0.05	9	0	0.5	1	0.5	50	0.668864381	0.340061435
442	0.05	9	0	0.5	3	0.5	50	0.670569056	0.342566878
443	0.05	9	0	0.5	5	0.5	50	0.66939503	0.343034974
444	0.05	9	0	0.5	7	0.5	50	0.672502642	0.350584952
445	0.05	9	0	0.5	9	0.5	50	0.670453441	0.346156483
446	0.05	9	0	0.5	11	0.5	50	0.672426711	0.352461603
447	0.05	9	0	0.5	13	0.5	50	0.672765642	0.353661783
448	0.05	9	0	0.5	15	0.5	50	0.675041429	0.358873827
449	0.05	9	0	0.5	17	0.5	50	0.674586064	0.358294965
450	0.05	9	0	0.5	19	0.5	50	0.67689508	0.364955779

#	eta	max_depth	gamma	colsample_bytree	min_child_weight	subsample	nrounds	Accuracy	Kappa
451	0.05	9	0.1	0.5	1	0.5	50	0.672349276	0.345395414
452	0.05	9	0.1	0.5	3	0.5	50	0.670495969	0.343604958
453	0.05	9	0.1	0.5	5	0.5	50	0.667578051	0.339055505
454	0.05	9	0.1	0.5	7	0.5	50	0.66912919	0.343546168
455	0.05	9	0.1	0.5	9	0.5	50	0.672047883	0.349665289
456	0.05	9	0.1	0.5	11	0.5	50	0.67110246	0.350113442
457	0.05	9	0.1	0.5	13	0.5	50	0.674889007	0.35815629
458	0.05	9	0.1	0.5	15	0.5	50	0.677843598	0.365089433
459	0.05	9	0.1	0.5	17	0.5	50	0.677235472	0.364678356
460	0.05	9	0.1	0.5	19	0.5	50	0.673598288	0.358226964
461	0.05	9	0.2	0.5	1	0.5	50	0.670152174	0.342073157
462	0.05	9	0.2	0.5	3	0.5	50	0.670610293	0.343261464
463	0.05	9	0.2	0.5	5	0.5	50	0.671859523	0.347679762
464	0.05	9	0.2	0.5	7	0.5	50	0.669319831	0.344034779
465	0.05	9	0.2	0.5	9	0.5	50	0.673409022	0.353845205
466	0.05	9	0.2	0.5	11	0.5	50	0.66852287	0.344976995
467	0.05	9	0.2	0.5	13	0.5	50	0.672575002	0.353169002
468	0.05	9	0.2	0.5	15	0.5	50	0.676138192	0.361883536
469	0.05	9	0.2	0.5	17	0.5	50	0.674584945	0.358703995
470	0.05	9	0.2	0.5	19	0.5	50	0.675833353	0.363482736
471	0.05	9	0.3	0.5	1	0.5	50	0.668752424	0.338076063
472	0.05	9	0.3	0.5	3	0.5	50	0.666327792	0.336346327
473	0.05	9	0.3	0.5	5	0.5	50	0.668562944	0.342330699
474	0.05	9	0.3	0.5	7	0.5	50	0.674357283	0.355158008
475	0.05	9	0.3	0.5	9	0.5	50	0.672465882	0.350253938
476	0.05	9	0.3	0.5	11	0.5	50	0.67113737	0.350294197
477	0.05	9	0.3	0.5	13	0.5	50	0.675494855	0.359958982
478	0.05	9	0.3	0.5	15	0.5	50	0.674661477	0.358195083
479	0.05	9	0.3	0.5	17	0.5	50	0.674015643	0.358388646
480	0.05	9	0.3	0.5	19	0.5	50	0.674621273	0.358745034
481	0.05	9	0.4	0.5	1	0.5	50	0.667806487	0.337129098
482	0.05	9	0.4	0.5	3	0.5	50	0.668334294	0.338910291
483	0.05	9	0.4	0.5	5	0.5	50	0.66966018	0.343869209
484	0.05	9	0.4	0.5	7	0.5	50	0.670872476	0.347099754
485	0.05	9	0.4	0.5	9	0.5	50	0.669169134	0.344699683
486	0.05	9	0.4	0.5	11	0.5	50	0.674886941	0.358233807
487	0.05	9	0.4	0.5	13	0.5	50	0.672803866	0.353191739
488	0.05	9	0.4	0.5	15	0.5	50	0.674736503	0.358916387
489	0.05	9	0.4	0.5	17	0.5	50	0.67674322	0.362300311
490	0.05	9	0.4	0.5	19	0.5	50	0.675304988	0.361416869
491	0.05	9	0.5	0.5	1	0.5	50	0.668902864	0.341138849
492	0.05	9	0.5	0.5	3	0.5	50	0.671593293	0.34534782
493	0.05	9	0.5	0.5	5	0.5	50	0.671593637	0.347104956
494	0.05	9	0.5	0.5	7	0.5	50	0.670721132	0.346427544
495	0.05	9	0.5	0.5	9	0.5	50	0.670417111	0.346947092
496	0.05	9	0.5	0.5	11	0.5	50	0.672881128	0.352278939
497	0.05	9	0.5	0.5	13	0.5	50	0.674319706	0.357054219
498	0.05	9	0.5	0.5	15	0.5	50	0.675796809	0.361161682
499	0.05	9	0.5	0.5	17	0.5	50	0.677464294	0.365236377
500	0.05	9	0.5	0.5	19	0.5	50	0.675760006	0.361793648
501	0.05	9	0.6	0.5	1	0.5	50	0.665985118	0.33328019
502	0.05	9	0.6	0.5	3	0.5	50	0.6691681	0.342185366
503	0.05	9	0.6	0.5	5	0.5	50	0.66856148	0.340930116
504	0.05	9	0.6	0.5	7	0.5	50	0.670758667	0.346653966
505	0.05	9	0.6	0.5	9	0.5	50	0.670040347	0.345648577
506	0.05	9	0.6	0.5	11	0.5	50	0.672391288	0.352282627
507	0.05	9	0.6	0.5	13	0.5	50	0.674128894	0.356940693
508	0.05	9	0.6	0.5	15	0.5	50	0.674395895	0.358032955
509	0.05	9	0.6	0.5	17	0.5	50	0.675228197	0.361014375
510	0.05	9	0.6	0.5	19	0.5	50	0.676022877	0.36298543
511	0.05	9	0.7	0.5	1	0.5	50	0.666554721	0.335324165
512	0.05	9	0.7	0.5	3	0.5	50	0.666856934	0.335692707
513	0.05	9	0.7	0.5	5	0.5	50	0.670341699	0.346076131
514	0.05	9	0.7	0.5	7	0.5	50	0.671365591	0.34712837
515	0.05	9	0.7	0.5	9	0.5	50	0.669471474	0.344119423
516	0.05	9	0.7	0.5	11	0.5	50	0.670909063	0.348179936
517	0.05	9	0.7	0.5	13	0.5	50	0.67587179	0.360312932
518	0.05	9	0.7	0.5	15	0.5	50	0.67484846	0.35885756
519	0.05	9	0.7	0.5	17	0.5	50	0.676022747	0.362315325
520	0.05	9	0.7	0.5	19	0.5	50	0.676743778	0.363776376
521	0.05	9	0.8	0.5	1	0.5	50	0.668939711	0.338503894
522	0.05	9	0.8	0.5	3	0.5	50	0.669469883	0.341630434
523	0.05	9	0.8	0.5	5	0.5	50	0.671403726	0.348299601
524	0.05	9	0.8	0.5	7	0.5	50	0.66943278	0.344395365
525	0.05	9	0.8	0.5	9	0.5	50	0.670797666	0.348029437
526	0.05	9	0.8	0.5	11	0.5	50	0.673901704	0.355002441
527	0.05	9	0.8	0.5	13	0.5	50	0.674546765	0.357840614
528	0.05	9	0.8	0.5	15	0.5	50	0.672386896	0.353520452
529	0.05	9	0.8	0.5	17	0.5	50	0.676062048	0.362123564
530	0.05	9	0.8	0.5	19	0.5	50	0.676818976	0.365111749
531	0.05	9	0.9	0.5	1	0.5	50	0.671406999	0.344571859
532	0.05	9	0.9	0.5	3	0.5	50	0.670267965	0.343372767
533	0.05	9	0.9	0.5	5	0.5	50	0.668865933	0.342127566
534	0.05	9	0.9	0.5	7	0.5	50	0.672462697	0.351687769
535	0.05	9	0.9	0.5	9	0.5	50	0.6726901	0.35333374
536	0.05	9	0.9	0.5	11	0.5	50	0.672879106	0.353639487
537	0.05	9	0.9	0.5	13	0.5	50	0.677465198	0.36344674
538	0.05	9	0.9	0.5	15	0.5	50	0.674584299	0.358460577
539	0.05	9	0.9	0.5	17	0.5	50	0.674053996	0.359063791
540	0.05	9	0.9	0.5	19	0.5	50	0.676026148	0.362262807
541	0.05	9	1	0.5	1	0.5	50	0.672008366	0.345594225
542	0.05	9	1	0.5	3	0.5	50	0.674246057	0.351186861
543	0.05	9	1	0.5	5	0.5	50	0.668407251	0.340409794
544	0.05	9	1	0.5	7	0.5	50	0.671176756	0.346991862
545	0.05	9	1	0.5	9	0.5	50	0.672804812	0.352577178
546	0.05	9	1	0.5	11	0.5	50	0.672462226	0.353092088
547	0.05	9	1	0.5	13	0.5	50	0.675608232	0.358809742
548	0.05	9	1	0.5	15	0.5	50	0.676364646	0.361905969
549	0.05	9	1	0.5	17	0.5	50	0.676328318	0.363688128
550	0.05	9	1	0.5	19	0.5	50	0.677351215	0.364189273
551	0.05	10	0	0.5	1	0.5	50	0.662805065	0.324958167
552	0.05	10	0	0.5	3	0.5	50	0.666100003	0.332748614
553	0.05	10	0	0.5	5	0.5	50	0.666100866	0.334402978
554	0.05	10	0	0.5	7	0.5	50	0.668827322	0.340603597
555	0.05	10	0	0.5	9	0.5	50	0.671173826	0.346881483
556	0.05	10	0	0.5	11	0.5	50	0.671023647	0.348600087
557	0.05	10	0	0.5	13	0.5	50	0.672614988	0.353715542
558	0.05	10	0	0.5	15	0.5	50	0.672576893	0.3519979
559	0.05	10	0	0.5	17	0.5	50	0.676934249	0.364606675
560	0.05	10	0	0.5	19	0.5	50	0.677084559	0.365637223
561	0.05	10	0.1	0.5	1	0.5	50	0.664851855	0.328756636
562	0.05	10	0.1	0.5	3	0.5	50	0.667426151	0.335989365
563	0.05	10	0.1	0.5	5	0.5	50	0.667160954	0.336573796
564	0.05	10	0.1	0.5	7	0.5	50	0.666477586	0.336892993
565	0.05	10	0.1	0.5	9	0.5	50	0.672616495	0.349578642
566	0.05	10	0.1	0.5	11	0.5	50	0.671552014	0.347419438
567	0.05	10	0.1	0.5	13	0.5	50	0.669621744	0.345591819
568	0.05	10	0.1	0.5	15	0.5	50	0.672084124	0.352492641
569	0.05	10	0.1	0.5	17	0.5	50	0.677655539	0.36531217
570	0.05	10	0.1	0.5	19	0.5	50	0.678486892	0.367655313
571	0.05	10	0.2	0.5	1	0.5	50	0.665076286	0.328510762
572	0.05	10	0.2	0.5	3	0.5	50	0.670872992	0.342617262
573	0.05	10	0.2	0.5	5	0.5	50	0.670416597	0.342784425
574	0.05	10	0.2	0.5	7	0.5	50	0.670188119	0.342629683
575	0.05	10	0.2	0.5	9	0.5	50	0.668559156	0.341504207
576	0.05	10	0.2	0.5	11	0.5	50	0.67132784	0.348941056
577	0.05	10	0.2	0.5	13	0.5	50	0.674245284	0.356316354
578	0.05	10	0.2	0.5	15	0.5	50	0.676366066	0.360706952
579	0.05	10	0.2	0.5	17	0.5	50	0.674470189	0.357993346
580	0.05	10	0.2	0.5	19	0.5	50	0.675379453	0.360268788
581	0.05	10	0.3	0.5	1	0.5	50	0.667804807	0.33436783
582	0.05	10	0.3	0.5	3	0.5	50	0.668071123	0.337344523
583	0.05	10	0.3	0.5	5	0.5	50	0.666253239	0.334620374
584	0.05	10	0.3	0.5	7	0.5	50	0.667802571	0.339509652
585	0.05	10	0.3	0.5	9	0.5	50	0.669584122	0.344569779
586	0.05	10	0.3	0.5	11	0.5	50	0.674434677	0.354718308
587	0.05	10	0.3	0.5	13	0.5	50	0.672084168	0.351344275
588	0.05	10	0.3	0.5	15	0.5	50	0.673105778	0.354294773
589	0.05	10	0.3	0.5	17	0.5	50	0.678259146	0.365765795
590	0.05	10	0.3	0.5	19	0.5	50	0.675380228	0.360894738
591	0.05	10	0.4	0.5	1	0.5	50	0.663825813	0.32521841
592	0.05	10	0.4	0.5	3	0.5	50	0.66901538	0.337975457
593	0.05	10	0.4	0.5	5	0.5	50	0.666818623	0.335649302
594	0.05	10	0.4	0.5	7	0.5	50	0.668296244	0.339190736
595	0.05	10	0.4	0.5	9	0.5	50	0.67261374	0.351749319
596	0.05	10	0.4	0.5	11	0.5	50	0.671023778	0.347308681
597	0.05	10	0.4	0.5	13	0.5	50	0.671857066	0.351556133
598	0.05	10	0.4	0.5	15	0.5	50	0.674584515	0.358732226
599	0.05	10	0.4	0.5	17	0.5	50	0.676135393	0.359514425
600	0.05	10	0.4	0.5	19	0.5	50	0.679054775	0.36870784

#	eta	max_depth	gamma	colsample_bytree	min_child_weight	subsample	nrounds	Accuracy	Kappa
601	0.05	10	0.5	0.5	1	0.5	50	0.66515299	0.327902763
602	0.05	10	0.5	0.5	3	0.5	50	0.668144942	0.337076697
603	0.05	10	0.5	0.5	5	0.5	50	0.667423522	0.336654162
604	0.05	10	0.5	0.5	7	0.5	50	0.668335673	0.339193583
605	0.05	10	0.5	0.5	9	0.5	50	0.670418275	0.34593544
606	0.05	10	0.5	0.5	11	0.5	50	0.672274636	0.349937013
607	0.05	10	0.5	0.5	13	0.5	50	0.672046419	0.352237664
608	0.05	10	0.5	0.5	15	0.5	50	0.674169698	0.357491744
609	0.05	10	0.5	0.5	17	0.5	50	0.675531442	0.360889647
610	0.05	10	0.5	0.5	19	0.5	50	0.677275975	0.363743445
611	0.05	10	0.6	0.5	1	0.5	50	0.666667539	0.330346039
612	0.05	10	0.6	0.5	3	0.5	50	0.67000221	0.34116488
613	0.05	10	0.6	0.5	5	0.5	50	0.670872648	0.343953603
614	0.05	10	0.6	0.5	7	0.5	50	0.669547966	0.342178317
615	0.05	10	0.6	0.5	9	0.5	50	0.668976725	0.341800604
616	0.05	10	0.6	0.5	11	0.5	50	0.670228622	0.346986887
617	0.05	10	0.6	0.5	13	0.5	50	0.6729927	0.352455153
618	0.05	10	0.6	0.5	15	0.5	50	0.672352032	0.353597176
619	0.05	10	0.6	0.5	17	0.5	50	0.677088175	0.363845918
620	0.05	10	0.6	0.5	19	0.5	50	0.676176242	0.363275171
621	0.05	10	0.7	0.5	1	0.5	50	0.66522806	0.329411147
622	0.05	10	0.7	0.5	3	0.5	50	0.667465059	0.336532605
623	0.05	10	0.7	0.5	5	0.5	50	0.669282814	0.340277348
624	0.05	10	0.7	0.5	7	0.5	50	0.670912033	0.345524135
625	0.05	10	0.7	0.5	9	0.5	50	0.670682996	0.345511702
626	0.05	10	0.7	0.5	11	0.5	50	0.669924129	0.346879351
627	0.05	10	0.7	0.5	13	0.5	50	0.672159538	0.352382421
628	0.05	10	0.7	0.5	15	0.5	50	0.674357501	0.357610711
629	0.05	10	0.7	0.5	17	0.5	50	0.675683559	0.361771048
630	0.05	10	0.7	0.5	19	0.5	50	0.675910015	0.361489493
631	0.05	10	0.8	0.5	1	0.5	50	0.6710623	0.34122494
632	0.05	10	0.8	0.5	3	0.5	50	0.665986925	0.331350691
633	0.05	10	0.8	0.5	5	0.5	50	0.668298652	0.33820512
634	0.05	10	0.8	0.5	7	0.5	50	0.668565355	0.340295076
635	0.05	10	0.8	0.5	9	0.5	50	0.669090235	0.343399347
636	0.05	10	0.8	0.5	11	0.5	50	0.672196298	0.351775311
637	0.05	10	0.8	0.5	13	0.5	50	0.672009616	0.351525272
638	0.05	10	0.8	0.5	15	0.5	50	0.676175423	0.3608864
639	0.05	10	0.8	0.5	17	0.5	50	0.674242917	0.357630784
640	0.05	10	0.8	0.5	19	0.5	50	0.677351132	0.364699274
641	0.05	10	0.9	0.5	1	0.5	50	0.667653894	0.334767241
642	0.05	10	0.9	0.5	3	0.5	50	0.66572199	0.331994485
643	0.05	10	0.9	0.5	5	0.5	50	0.667651614	0.337582031
644	0.05	10	0.9	0.5	7	0.5	50	0.671705852	0.347651446
645	0.05	10	0.9	0.5	9	0.5	50	0.669393607	0.343702411
646	0.05	10	0.9	0.5	11	0.5	50	0.671668492	0.350044764
647	0.05	10	0.9	0.5	13	0.5	50	0.673751998	0.355633238
648	0.05	10	0.9	0.5	15	0.5	50	0.675534024	0.361469421
649	0.05	10	0.9	0.5	17	0.5	50	0.674434419	0.356918451
650	0.05	10	0.9	0.5	19	0.5	50	0.675834945	0.363001261
651	0.05	10	1	0.5	1	0.5	50	0.66799601	0.336214458
652	0.05	10	1	0.5	3	0.5	50	0.669280661	0.338528526
653	0.05	10	1	0.5	5	0.5	50	0.669811955	0.342030317
654	0.05	10	1	0.5	7	0.5	50	0.667462737	0.339160644
655	0.05	10	1	0.5	9	0.5	50	0.670416553	0.345907927
656	0.05	10	1	0.5	11	0.5	50	0.670683039	0.347030146
657	0.05	10	1	0.5	13	0.5	50	0.670758968	0.349439599
658	0.05	10	1	0.5	15	0.5	50	0.670381472	0.349365989
659	0.05	10	1	0.5	17	0.5	50	0.674168493	0.357217536
660	0.05	10	1	0.5	19	0.5	50	0.676554774	0.362009195
661	0.05	5	0	0.5	1	0.5	100	0.678750797	0.373517633
662	0.05	5	0	0.5	3	0.5	100	0.67799434	0.372769007
663	0.05	5	0	0.5	5	0.5	100	0.680835421	0.377961363
664	0.05	5	0	0.5	7	0.5	100	0.677653645	0.371490834
665	0.05	5	0	0.5	9	0.5	100	0.680077201	0.376339629
666	0.05	5	0	0.5	11	0.5	100	0.679358493	0.375133096
667	0.05	5	0	0.5	13	0.5	100	0.677046551	0.371620722
668	0.05	5	0	0.5	15	0.5	100	0.67981248	0.377118244
669	0.05	5	0	0.5	17	0.5	100	0.681176548	0.379833919
670	0.05	5	0	0.5	19	0.5	100	0.681781833	0.381156033
671	0.05	5	0.1	0.5	1	0.5	100	0.678219763	0.373233627
672	0.05	5	0.1	0.5	3	0.5	100	0.680152226	0.376251355
673	0.05	5	0.1	0.5	5	0.5	100	0.678295433	0.373007934
674	0.05	5	0.1	0.5	7	0.5	100	0.675644734	0.368282975
675	0.05	5	0.1	0.5	9	0.5	100	0.680529895	0.377501932
676	0.05	5	0.1	0.5	11	0.5	100	0.677765861	0.373147591
677	0.05	5	0.1	0.5	13	0.5	100	0.67803226	0.373074701
678	0.05	5	0.1	0.5	15	0.5	100	0.679659112	0.376684968
679	0.05	5	0.1	0.5	17	0.5	100	0.680985646	0.379865207
680	0.05	5	0.1	0.5	19	0.5	100	0.681253425	0.380092511
681	0.05	5	0.2	0.5	1	0.5	100	0.675153643	0.366549465
682	0.05	5	0.2	0.5	3	0.5	100	0.679469892	0.375002607
683	0.05	5	0.2	0.5	5	0.5	100	0.678827588	0.374588589
684	0.05	5	0.2	0.5	7	0.5	100	0.678409629	0.372904562
685	0.05	5	0.2	0.5	9	0.5	100	0.677766807	0.372227019
686	0.05	5	0.2	0.5	11	0.5	100	0.679926288	0.376777092
687	0.05	5	0.2	0.5	13	0.5	100	0.680758892	0.377925226
688	0.05	5	0.2	0.5	15	0.5	100	0.678865638	0.375222878
689	0.05	5	0.2	0.5	17	0.5	100	0.681252435	0.380061952
690	0.05	5	0.2	0.5	19	0.5	100	0.680379758	0.378709755
691	0.05	5	0.3	0.5	1	0.5	100	0.678941867	0.373896772
692	0.05	5	0.3	0.5	3	0.5	100	0.679736937	0.375785003
693	0.05	5	0.3	0.5	5	0.5	100	0.677767454	0.371655573
694	0.05	5	0.3	0.5	7	0.5	100	0.679092479	0.37476615
695	0.05	5	0.3	0.5	9	0.5	100	0.680987153	0.378686996
696	0.05	5	0.3	0.5	11	0.5	100	0.677349754	0.372112753
697	0.05	5	0.3	0.5	13	0.5	100	0.680154078	0.377588054
698	0.05	5	0.3	0.5	15	0.5	100	0.679736206	0.377118262
699	0.05	5	0.3	0.5	17	0.5	100	0.679244556	0.375952742
700	0.05	5	0.3	0.5	19	0.5	100	0.679358322	0.376183677
701	0.05	5	0.4	0.5	1	0.5	100	0.677764269	0.371682599
702	0.05	5	0.4	0.5	3	0.5	100	0.678297543	0.372534626
703	0.05	5	0.4	0.5	5	0.5	100	0.678599324	0.373300326
704	0.05	5	0.4	0.5	7	0.5	100	0.677388193	0.3708233
705	0.05	5	0.4	0.5	9	0.5	100	0.680457022	0.378136106
706	0.05	5	0.4	0.5	11	0.5	100	0.678674221	0.373904707
707	0.05	5	0.4	0.5	13	0.5	100	0.679583442	0.376547929
708	0.05	5	0.4	0.5	15	0.5	100	0.679546682	0.376042675
709	0.05	5	0.4	0.5	17	0.5	100	0.679319883	0.376061842
710	0.05	5	0.4	0.5	19	0.5	100	0.678638279	0.37461699
711	0.05	5	0.5	0.5	1	0.5	100	0.679282735	0.374363144
712	0.05	5	0.5	0.5	3	0.5	100	0.679431152	0.374663806
713	0.05	5	0.5	0.5	5	0.5	100	0.677652182	0.371966874
714	0.05	5	0.5	0.5	7	0.5	100	0.680417638	0.377427265
715	0.05	5	0.5	0.5	9	0.5	100	0.680038892	0.376233449
716	0.05	5	0.5	0.5	11	0.5	100	0.678598635	0.373995047
717	0.05	5	0.5	0.5	13	0.5	100	0.679168325	0.375918429
718	0.05	5	0.5	0.5	15	0.5	100	0.679963392	0.377332538
719	0.05	5	0.5	0.5	17	0.5	100	0.680872914	0.379394597
720	0.05	5	0.5	0.5	19	0.5	100	0.678939847	0.375850211
721	0.05	5	0.6	0.5	1	0.5	100	0.679054343	0.374299939
722	0.05	5	0.6	0.5	3	0.5	100	0.675759662	0.367828405
723	0.05	5	0.6	0.5	5	0.5	100	0.67693115	0.370396141
724	0.05	5	0.6	0.5	7	0.5	100	0.677840673	0.372269119
725	0.05	5	0.6	0.5	9	0.5	100	0.681629415	0.379554172
726	0.05	5	0.6	0.5	11	0.5	100	0.679508544	0.375851282
727	0.05	5	0.6	0.5	13	0.5	100	0.678902011	0.375466419
728	0.05	5	0.6	0.5	15	0.5	100	0.67981235	0.377685124
729	0.05	5	0.6	0.5	17	0.5	100	0.680682186	0.379319345
730	0.05	5	0.6	0.5	19	0.5	100	0.681554346	0.380958477
731	0.05	5	0.7	0.5	1	0.5	100	0.679168367	0.374520063
732	0.05	5	0.7	0.5	3	0.5	100	0.678863529	0.373730171
733	0.05	5	0.7	0.5	5	0.5	100	0.679814416	0.376585514
734	0.05	5	0.7	0.5	7	0.5	100	0.678220148	0.373148058
735	0.05	5	0.7	0.5	9	0.5	100	0.678408726	0.373192706
736	0.05	5	0.7	0.5	11	0.5	100	0.678145683	0.372868546
737	0.05	5	0.7	0.5	13	0.5	100	0.680153865	0.37822632
738	0.05	5	0.7	0.5	15	0.5	100	0.681328192	0.380385577
739	0.05	5	0.7	0.5	17	0.5	100	0.681743395	0.381153325
740	0.05	5	0.7	0.5	19	0.5	100	0.680456721	0.378442446
741	0.05	5	0.8	0.5	1	0.5	100	0.680229191	0.376722526
742	0.05	5	0.8	0.5	3	0.5	100	0.677161436	0.370829818
743	0.05	5	0.8	0.5	5	0.5	100	0.679319839	0.375291544
744	0.05	5	0.8	0.5	7	0.5	100	0.679506694	0.376102215
745	0.05	5	0.8	0.5	9	0.5	100	0.679357459	0.375383139
746	0.05	5	0.8	0.5	11	0.5	100	0.67916656	0.375263305
747	0.05	5	0.8	0.5	13	0.5	100	0.681252435	0.379800141
748	0.05	5	0.8	0.5	15	0.5	100	0.680077847	0.377596118
749	0.05	5	0.8	0.5	17	0.5	100	0.680303054	0.377870107
750	0.05	5	0.8	0.5	19	0.5	100	0.680758417	0.378810202

#	eta	max_depth	gamma	colsample_bytree	min_child_weight	subsample	nrounds	Accuracy	Kappa
751	0.05	5	0.9	0.5	1	0.5	100	0.678523264	0.37381328
752	0.05	5	0.9	0.5	3	0.5	100	0.679092136	0.374576461
753	0.05	5	0.9	0.5	5	0.5	100	0.68102301	0.378761673
754	0.05	5	0.9	0.5	7	0.5	100	0.677388279	0.371472165
755	0.05	5	0.9	0.5	9	0.5	100	0.679697723	0.376246213
756	0.05	5	0.9	0.5	11	0.5	100	0.680266465	0.3777343
757	0.05	5	0.9	0.5	13	0.5	100	0.679016335	0.375604733
758	0.05	5	0.9	0.5	15	0.5	100	0.680872742	0.379206843
759	0.05	5	0.9	0.5	17	0.5	100	0.681403691	0.380230288
760	0.05	5	0.9	0.5	19	0.5	100	0.678598981	0.375470464
761	0.05	5	1	0.5	1	0.5	100	0.676553438	0.369627301
762	0.05	5	1	0.5	3	0.5	100	0.679205903	0.374157496
763	0.05	5	1	0.5	5	0.5	100	0.68087313	0.378631364
764	0.05	5	1	0.5	7	0.5	100	0.678031787	0.372823236
765	0.05	5	1	0.5	9	0.5	100	0.677652095	0.372697758
766	0.05	5	1	0.5	11	0.5	100	0.680418669	0.37774116
767	0.05	5	1	0.5	13	0.5	100	0.680454698	0.378412207
768	0.05	5	1	0.5	15	0.5	100	0.679662385	0.376822861
769	0.05	5	1	0.5	17	0.5	100	0.680305033	0.378193921
770	0.05	5	1	0.5	19	0.5	100	0.681478416	0.380558119
771	0.05	6	0	0.5	1	0.5	100	0.675266591	0.362636261
772	0.05	6	0	0.5	3	0.5	100	0.678260135	0.368727846
773	0.05	6	0	0.5	5	0.5	100	0.677009188	0.367404328
774	0.05	6	0	0.5	7	0.5	100	0.673486846	0.360520143
775	0.05	6	0	0.5	9	0.5	100	0.679885611	0.373447715
776	0.05	6	0	0.5	11	0.5	100	0.676363913	0.366058789
777	0.05	6	0	0.5	13	0.5	100	0.675570698	0.365312115
778	0.05	6	0	0.5	15	0.5	100	0.676402698	0.367658976
779	0.05	6	0	0.5	17	0.5	100	0.677539578	0.370415863
780	0.05	6	0	0.5	19	0.5	100	0.678790053	0.37312572
781	0.05	6	0.1	0.5	1	0.5	100	0.675985642	0.363677214
782	0.05	6	0.1	0.5	3	0.5	100	0.677955298	0.368252527
783	0.05	6	0.1	0.5	5	0.5	100	0.67557048	0.364051541
784	0.05	6	0.1	0.5	7	0.5	100	0.673484176	0.36012428
785	0.05	6	0.1	0.5	9	0.5	100	0.6735982	0.360096475
786	0.05	6	0.1	0.5	11	0.5	100	0.675759619	0.366121123
787	0.05	6	0.1	0.5	13	0.5	100	0.677159283	0.368844248
788	0.05	6	0.1	0.5	15	0.5	100	0.676363527	0.366955907
789	0.05	6	0.1	0.5	17	0.5	100	0.679358019	0.37424536
790	0.05	6	0.1	0.5	19	0.5	100	0.677766765	0.371141077
791	0.05	6	0.2	0.5	1	0.5	100	0.673182695	0.358403102
792	0.05	6	0.2	0.5	3	0.5	100	0.675986632	0.364279997
793	0.05	6	0.2	0.5	5	0.5	100	0.677195397	0.367169716
794	0.05	6	0.2	0.5	7	0.5	100	0.675722257	0.364764369
795	0.05	6	0.2	0.5	9	0.5	100	0.675191091	0.364580879
796	0.05	6	0.2	0.5	11	0.5	100	0.675494767	0.364477168
797	0.05	6	0.2	0.5	13	0.5	100	0.677955816	0.369980002
798	0.05	6	0.2	0.5	15	0.5	100	0.675871876	0.366002926
799	0.05	6	0.2	0.5	17	0.5	100	0.678827543	0.372459005
800	0.05	6	0.2	0.5	19	0.5	100	0.676781873	0.369522586
801	0.05	6	0.3	0.5	1	0.5	100	0.675265816	0.362236288
802	0.05	6	0.3	0.5	3	0.5	100	0.676665953	0.366016691
803	0.05	6	0.3	0.5	5	0.5	100	0.675038541	0.362629857
804	0.05	6	0.3	0.5	7	0.5	100	0.675417331	0.364224778
805	0.05	6	0.3	0.5	9	0.5	100	0.674433472	0.362420162
806	0.05	6	0.3	0.5	11	0.5	100	0.677236117	0.368129944
807	0.05	6	0.3	0.5	13	0.5	100	0.676363829	0.367284001
808	0.05	6	0.3	0.5	15	0.5	100	0.678525202	0.371571283
809	0.05	6	0.3	0.5	17	0.5	100	0.679963005	0.374810366
810	0.05	6	0.3	0.5	19	0.5	100	0.678028989	0.371684027
811	0.05	6	0.4	0.5	1	0.5	100	0.674737105	0.361133654
812	0.05	6	0.4	0.5	3	0.5	100	0.675682311	0.364336236
813	0.05	6	0.4	0.5	5	0.5	100	0.676252514	0.365682006
814	0.05	6	0.4	0.5	7	0.5	100	0.676971956	0.367170047
815	0.05	6	0.4	0.5	9	0.5	100	0.677918238	0.369430041
816	0.05	6	0.4	0.5	11	0.5	100	0.678446906	0.371011982
817	0.05	6	0.4	0.5	13	0.5	100	0.677955385	0.370434599
818	0.05	6	0.4	0.5	15	0.5	100	0.678296509	0.370745016
819	0.05	6	0.4	0.5	17	0.5	100	0.679245675	0.373626409
820	0.05	6	0.4	0.5	19	0.5	100	0.678637763	0.373128373
821	0.05	6	0.5	0.5	1	0.5	100	0.675114946	0.362005716
822	0.05	6	0.5	0.5	3	0.5	100	0.675795387	0.363496411
823	0.05	6	0.5	0.5	5	0.5	100	0.676401663	0.365560177
824	0.05	6	0.5	0.5	7	0.5	100	0.674470532	0.361471551
825	0.05	6	0.5	0.5	9	0.5	100	0.67515218	0.363539311
826	0.05	6	0.5	0.5	11	0.5	100	0.678070699	0.370255189
827	0.05	6	0.5	0.5	13	0.5	100	0.678296164	0.370380242
828	0.05	6	0.5	0.5	15	0.5	100	0.67549326	0.365870127
829	0.05	6	0.5	0.5	17	0.5	100	0.680190622	0.375383001
830	0.05	6	0.5	0.5	19	0.5	100	0.678903216	0.373319641
831	0.05	6	0.6	0.5	1	0.5	100	0.677351001	0.366944445
832	0.05	6	0.6	0.5	3	0.5	100	0.678220104	0.369146522
833	0.05	6	0.6	0.5	5	0.5	100	0.675457403	0.36338205
834	0.05	6	0.6	0.5	7	0.5	100	0.674015815	0.361541679
835	0.05	6	0.6	0.5	9	0.5	100	0.674813165	0.363500152
836	0.05	6	0.6	0.5	11	0.5	100	0.676931538	0.367398082
837	0.05	6	0.6	0.5	13	0.5	100	0.676288372	0.366608256
838	0.05	6	0.6	0.5	15	0.5	100	0.677992876	0.370650516
839	0.05	6	0.6	0.5	17	0.5	100	0.678827242	0.37314217
840	0.05	6	0.6	0.5	19	0.5	100	0.678561575	0.372350527
841	0.05	6	0.7	0.5	1	0.5	100	0.674167847	0.36106414
842	0.05	6	0.7	0.5	3	0.5	100	0.677235902	0.366059808
843	0.05	6	0.7	0.5	5	0.5	100	0.675342564	0.363857447
844	0.05	6	0.7	0.5	7	0.5	100	0.675491496	0.363717343
845	0.05	6	0.7	0.5	9	0.5	100	0.67515192	0.362932646
846	0.05	6	0.7	0.5	11	0.5	100	0.676668279	0.367276618
847	0.05	6	0.7	0.5	13	0.5	100	0.677047928	0.368265734
848	0.05	6	0.7	0.5	15	0.5	100	0.677274772	0.368741146
849	0.05	6	0.7	0.5	17	0.5	100	0.677123256	0.369674897
850	0.05	6	0.7	0.5	19	0.5	100	0.678904463	0.373208914
851	0.05	6	0.8	0.5	1	0.5	100	0.673297021	0.358876277
852	0.05	6	0.8	0.5	3	0.5	100	0.674887243	0.362736263
853	0.05	6	0.8	0.5	5	0.5	100	0.674547237	0.362127242
854	0.05	6	0.8	0.5	7	0.5	100	0.675455425	0.364084024
855	0.05	6	0.8	0.5	9	0.5	100	0.676328964	0.366058399
856	0.05	6	0.8	0.5	11	0.5	100	0.677801414	0.369648171
857	0.05	6	0.8	0.5	13	0.5	100	0.675606812	0.365961019
858	0.05	6	0.8	0.5	15	0.5	100	0.679320356	0.373026643
859	0.05	6	0.8	0.5	17	0.5	100	0.678562349	0.372232699
860	0.05	6	0.8	0.5	19	0.5	100	0.679660835	0.374854799
861	0.05	6	0.9	0.5	1	0.5	100	0.676176543	0.363643816
862	0.05	6	0.9	0.5	3	0.5	100	0.675948107	0.364558575
863	0.05	6	0.9	0.5	5	0.5	100	0.675759532	0.364480636
864	0.05	6	0.9	0.5	7	0.5	100	0.674697247	0.362580341
865	0.05	6	0.9	0.5	9	0.5	100	0.674811915	0.363345239
866	0.05	6	0.9	0.5	11	0.5	100	0.675834772	0.365650397
867	0.05	6	0.9	0.5	13	0.5	100	0.676668236	0.368510974
868	0.05	6	0.9	0.5	15	0.5	100	0.67788152	0.370617297
869	0.05	6	0.9	0.5	17	0.5	100	0.67625256	0.367611702
870	0.05	6	0.9	0.5	19	0.5	100	0.677387891	0.370224301
871	0.05	6	1	0.5	1	0.5	100	0.676177016	0.365091127
872	0.05	6	1	0.5	3	0.5	100	0.675685324	0.363655944
873	0.05	6	1	0.5	5	0.5	100	0.676402353	0.366092003
874	0.05	6	1	0.5	7	0.5	100	0.675190403	0.363714471
875	0.05	6	1	0.5	9	0.5	100	0.675301543	0.364568809
876	0.05	6	1	0.5	11	0.5	100	0.676440877	0.367233469
877	0.05	6	1	0.5	13	0.5	100	0.678448024	0.371412847
878	0.05	6	1	0.5	15	0.5	100	0.676173962	0.367161767
879	0.05	6	1	0.5	17	0.5	100	0.675948237	0.367248573
880	0.05	6	1	0.5	19	0.5	100	0.67799391	0.371811256
881	0.05	7	0	0.5	1	0.5	100	0.673601127	0.35489049
882	0.05	7	0	0.5	3	0.5	100	0.672955853	0.354760256
883	0.05	7	0	0.5	5	0.5	100	0.673562558	0.356933016
884	0.05	7	0	0.5	7	0.5	100	0.670798742	0.351539075
885	0.05	7	0	0.5	9	0.5	100	0.671403079	0.353225564
886	0.05	7	0	0.5	11	0.5	100	0.673447546	0.358501825
887	0.05	7	0	0.5	13	0.5	100	0.675190877	0.362587289
888	0.05	7	0	0.5	15	0.5	100	0.673826377	0.35988086
889	0.05	7	0	0.5	17	0.5	100	0.678336195	0.369152031
890	0.05	7	0	0.5	19	0.5	100	0.675949056	0.365676925
891	0.05	7	0.1	0.5	1	0.5	100	0.674208394	0.357079503
892	0.05	7	0.1	0.5	3	0.5	100	0.671253372	0.35057644
893	0.05	7	0.1	0.5	5	0.5	100	0.673184417	0.355110023
894	0.05	7	0.1	0.5	7	0.5	100	0.675115805	0.360260988
895	0.05	7	0.1	0.5	9	0.5	100	0.674625362	0.359031359
896	0.05	7	0.1	0.5	11	0.5	100	0.6736768	0.357962403
897	0.05	7	0.1	0.5	13	0.5	100	0.673750835	0.359185781
898	0.05	7	0.1	0.5	15	0.5	100	0.675002816	0.362128121
899	0.05	7	0.1	0.5	17	0.5	100	0.675910617	0.364353688
900	0.05	7	0.1	0.5	19	0.5	100	0.676935843	0.367275827

#	eta	max_depth	gamma	colsample_bytree	min_child_weight	subsample	nrounds	Accuracy	Kappa
901	0.05	7	0.2	0.5	1	0.5	100	0.673524938	0.355325988
902	0.05	7	0.2	0.5	3	0.5	100	0.671632074	0.351966531
903	0.05	7	0.2	0.5	5	0.5	100	0.673374371	0.355508421
904	0.05	7	0.2	0.5	7	0.5	100	0.673978151	0.357880202
905	0.05	7	0.2	0.5	9	0.5	100	0.673559891	0.357872913
906	0.05	7	0.2	0.5	11	0.5	100	0.675911308	0.36324166
907	0.05	7	0.2	0.5	13	0.5	100	0.675493905	0.362226116
908	0.05	7	0.2	0.5	15	0.5	100	0.676023048	0.364575146
909	0.05	7	0.2	0.5	17	0.5	100	0.673370498	0.359721734
910	0.05	7	0.2	0.5	19	0.5	100	0.67772936	0.368821886
911	0.05	7	0.3	0.5	1	0.5	100	0.674320223	0.356443841
912	0.05	7	0.3	0.5	3	0.5	100	0.67204659	0.35328995
913	0.05	7	0.3	0.5	5	0.5	100	0.674283591	0.358066436
914	0.05	7	0.3	0.5	7	0.5	100	0.672955854	0.355373419
915	0.05	7	0.3	0.5	9	0.5	100	0.671628718	0.353569171
916	0.05	7	0.3	0.5	11	0.5	100	0.674091874	0.359608355
917	0.05	7	0.3	0.5	13	0.5	100	0.67424425	0.360704153
918	0.05	7	0.3	0.5	15	0.5	100	0.676024684	0.364281932
919	0.05	7	0.3	0.5	17	0.5	100	0.673752127	0.360595145
920	0.05	7	0.3	0.5	19	0.5	100	0.677122352	0.367912504
921	0.05	7	0.4	0.5	1	0.5	100	0.672274854	0.352546503
922	0.05	7	0.4	0.5	3	0.5	100	0.672656482	0.35424026
923	0.05	7	0.4	0.5	5	0.5	100	0.673675766	0.356561508
924	0.05	7	0.4	0.5	7	0.5	100	0.674547409	0.35909898
925	0.05	7	0.4	0.5	9	0.5	100	0.674737147	0.359900732
926	0.05	7	0.4	0.5	11	0.5	100	0.673598889	0.358801098
927	0.05	7	0.4	0.5	13	0.5	100	0.673259099	0.358503142
928	0.05	7	0.4	0.5	15	0.5	100	0.675303953	0.363239869
929	0.05	7	0.4	0.5	17	0.5	100	0.6755317	0.364050476
930	0.05	7	0.4	0.5	19	0.5	100	0.675570484	0.364990379
931	0.05	7	0.5	0.5	1	0.5	100	0.673562001	0.355026059
932	0.05	7	0.5	0.5	3	0.5	100	0.673677874	0.355480916
933	0.05	7	0.5	0.5	5	0.5	100	0.672387456	0.354176068
934	0.05	7	0.5	0.5	7	0.5	100	0.676288758	0.363139991
935	0.05	7	0.5	0.5	9	0.5	100	0.672199698	0.355037156
936	0.05	7	0.5	0.5	11	0.5	100	0.673788757	0.358995685
937	0.05	7	0.5	0.5	13	0.5	100	0.674396411	0.360603649
938	0.05	7	0.5	0.5	15	0.5	100	0.673905709	0.360839796
939	0.05	7	0.5	0.5	17	0.5	100	0.678487582	0.370098281
940	0.05	7	0.5	0.5	19	0.5	100	0.67602305	0.365686784
941	0.05	7	0.6	0.5	1	0.5	100	0.671060837	0.350298448
942	0.05	7	0.6	0.5	3	0.5	100	0.673448709	0.355436988
943	0.05	7	0.6	0.5	5	0.5	100	0.67075828	0.350660324
944	0.05	7	0.6	0.5	7	0.5	100	0.673674088	0.357241069
945	0.05	7	0.6	0.5	9	0.5	100	0.670911474	0.352172073
946	0.05	7	0.6	0.5	11	0.5	100	0.67454784	0.359978312
947	0.05	7	0.6	0.5	13	0.5	100	0.675191737	0.361919592
948	0.05	7	0.6	0.5	15	0.5	100	0.674736632	0.361698416
949	0.05	7	0.6	0.5	17	0.5	100	0.677652354	0.368949565
950	0.05	7	0.6	0.5	19	0.5	100	0.67632707	0.366688331
951	0.05	7	0.7	0.5	1	0.5	100	0.671063851	0.350191876
952	0.05	7	0.7	0.5	3	0.5	100	0.673525414	0.356041988
953	0.05	7	0.7	0.5	5	0.5	100	0.672160225	0.354268272
954	0.05	7	0.7	0.5	7	0.5	100	0.673790565	0.357347063
955	0.05	7	0.7	0.5	9	0.5	100	0.675456242	0.361951854
956	0.05	7	0.7	0.5	11	0.5	100	0.675949357	0.363280243
957	0.05	7	0.7	0.5	13	0.5	100	0.67337364	0.359267761
958	0.05	7	0.7	0.5	15	0.5	100	0.676479961	0.365923944
959	0.05	7	0.7	0.5	17	0.5	100	0.67465799	0.362501326
960	0.05	7	0.7	0.5	19	0.5	100	0.676213346	0.365884008
961	0.05	7	0.8	0.5	1	0.5	100	0.672047794	0.352412951
962	0.05	7	0.8	0.5	3	0.5	100	0.672842089	0.353952632
963	0.05	7	0.8	0.5	5	0.5	100	0.672312516	0.35424411
964	0.05	7	0.8	0.5	7	0.5	100	0.674129925	0.357939154
965	0.05	7	0.8	0.5	9	0.5	100	0.671858875	0.354437131
966	0.05	7	0.8	0.5	11	0.5	100	0.67121416	0.353491805
967	0.05	7	0.8	0.5	13	0.5	100	0.673866453	0.359524007
968	0.05	7	0.8	0.5	15	0.5	100	0.677007381	0.366991879
969	0.05	7	0.8	0.5	17	0.5	100	0.674849321	0.362896076
970	0.05	7	0.8	0.5	19	0.5	100	0.676439975	0.366762266
971	0.05	7	0.9	0.5	1	0.5	100	0.670952151	0.350252012
972	0.05	7	0.9	0.5	3	0.5	100	0.674168362	0.357735476
973	0.05	7	0.9	0.5	5	0.5	100	0.6724633	0.353960855
974	0.05	7	0.9	0.5	7	0.5	100	0.673221048	0.355469054
975	0.05	7	0.9	0.5	9	0.5	100	0.672879749	0.356666256
976	0.05	7	0.9	0.5	11	0.5	100	0.675759704	0.362864391
977	0.05	7	0.9	0.5	13	0.5	100	0.677083441	0.366387505
978	0.05	7	0.9	0.5	15	0.5	100	0.678636988	0.369251157
979	0.05	7	0.9	0.5	17	0.5	100	0.673980692	0.361358488
980	0.05	7	0.9	0.5	19	0.5	100	0.67681902	0.368078653
981	0.05	7	1	0.5	1	0.5	100	0.669847811	0.347595356
982	0.05	7	1	0.5	3	0.5	100	0.672840968	0.354509472
983	0.05	7	1	0.5	5	0.5	100	0.671742484	0.353489436
984	0.05	7	1	0.5	7	0.5	100	0.673108315	0.356516168
985	0.05	7	1	0.5	9	0.5	100	0.674319705	0.359583776
986	0.05	7	1	0.5	11	0.5	100	0.67367607	0.358983495
987	0.05	7	1	0.5	13	0.5	100	0.674092218	0.360041035
988	0.05	7	1	0.5	15	0.5	100	0.675076766	0.362066181
989	0.05	7	1	0.5	17	0.5	100	0.676744812	0.365958237
990	0.05	7	1	0.5	19	0.5	100	0.677426631	0.369113731
991	0.05	8	0	0.5	1	0.5	100	0.669512497	0.34314416
992	0.05	8	0	0.5	3	0.5	100	0.66833412	0.341984189
993	0.05	8	0	0.5	5	0.5	100	0.672502254	0.350882953
994	0.05	8	0	0.5	7	0.5	100	0.669280102	0.345665308
995	0.05	8	0	0.5	9	0.5	100	0.668713383	0.34560629
996	0.05	8	0	0.5	11	0.5	100	0.673866839	0.356731351
997	0.05	8	0	0.5	13	0.5	100	0.67280365	0.355041332
998	0.05	8	0	0.5	15	0.5	100	0.672159624	0.355369614
999	0.05	8	0	0.5	17	0.5	100	0.672577109	0.356479687
1000	0.05	8	0	0.5	19	0.5	100	0.674131001	0.360611763
1001	0.05	8	0.1	0.5	1	0.5	100	0.667956968	0.339883835
1002	0.05	8	0.1	0.5	3	0.5	100	0.669699826	0.344469443
1003	0.05	8	0.1	0.5	5	0.5	100	0.669963944	0.346670571
1004	0.05	8	0.1	0.5	7	0.5	100	0.668751994	0.344615294
1005	0.05	8	0.1	0.5	9	0.5	100	0.671100051	0.350822129
1006	0.05	8	0.1	0.5	11	0.5	100	0.671441821	0.351253938
1007	0.05	8	0.1	0.5	13	0.5	100	0.670154157	0.350442598
1008	0.05	8	0.1	0.5	15	0.5	100	0.675342865	0.361935605
1009	0.05	8	0.1	0.5	17	0.5	100	0.676707536	0.364789848
1010	0.05	8	0.1	0.5	19	0.5	100	0.676365938	0.364575749
1011	0.05	8	0.2	0.5	1	0.5	100	0.669357581	0.343056305
1012	0.05	8	0.2	0.5	3	0.5	100	0.67170637	0.34881637
1013	0.05	8	0.2	0.5	5	0.5	100	0.670684244	0.347435649
1014	0.05	8	0.2	0.5	7	0.5	100	0.673903685	0.354794766
1015	0.05	8	0.2	0.5	9	0.5	100	0.672084597	0.352421068
1016	0.05	8	0.2	0.5	11	0.5	100	0.67185853	0.352263799
1017	0.05	8	0.2	0.5	13	0.5	100	0.674093078	0.358029799
1018	0.05	8	0.2	0.5	15	0.5	100	0.673639869	0.358263865
1019	0.05	8	0.2	0.5	17	0.5	100	0.674246532	0.360449969
1020	0.05	8	0.2	0.5	19	0.5	100	0.675569665	0.363432773
1021	0.05	8	0.3	0.5	1	0.5	100	0.668446637	0.341427747
1022	0.05	8	0.3	0.5	3	0.5	100	0.668337177	0.341680957
1023	0.05	8	0.3	0.5	5	0.5	100	0.669622129	0.344498547
1024	0.05	8	0.3	0.5	7	0.5	100	0.669776271	0.346471336
1025	0.05	8	0.3	0.5	9	0.5	100	0.671970876	0.351718019
1026	0.05	8	0.3	0.5	11	0.5	100	0.671706845	0.35236197
1027	0.05	8	0.3	0.5	13	0.5	100	0.67367796	0.357480774
1028	0.05	8	0.3	0.5	15	0.5	100	0.674245369	0.35920359
1029	0.05	8	0.3	0.5	17	0.5	100	0.675531355	0.363054527
1030	0.05	8	0.3	0.5	19	0.5	100	0.673865851	0.359978123
1031	0.05	8	0.4	0.5	1	0.5	100	0.669508923	0.343585879
1032	0.05	8	0.4	0.5	3	0.5	100	0.669396192	0.344048548
1033	0.05	8	0.4	0.5	5	0.5	100	0.673676498	0.353801353
1034	0.05	8	0.4	0.5	7	0.5	100	0.673070954	0.353745033
1035	0.05	8	0.4	0.5	9	0.5	100	0.672463728	0.352818899
1036	0.05	8	0.4	0.5	11	0.5	100	0.674435236	0.358067273
1037	0.05	8	0.4	0.5	13	0.5	100	0.674775671	0.359443384
1038	0.05	8	0.4	0.5	15	0.5	100	0.675344844	0.361931547
1039	0.05	8	0.4	0.5	17	0.5	100	0.675985987	0.363383199
1040	0.05	8	0.4	0.5	19	0.5	100	0.67617452	0.364375956
1041	0.05	8	0.5	0.5	1	0.5	100	0.669545425	0.344010192
1042	0.05	8	0.5	0.5	3	0.5	100	0.668067936	0.341141333
1043	0.05	8	0.5	0.5	5	0.5	100	0.669510818	0.344663717
1044	0.05	8	0.5	0.5	7	0.5	100	0.671064925	0.349332723
1045	0.05	8	0.5	0.5	9	0.5	100	0.670116837	0.347667534
1046	0.05	8	0.5	0.5	11	0.5	100	0.675418836	0.359698187
1047	0.05	8	0.5	0.5	13	0.5	100	0.673676541	0.357450034
1048	0.05	8	0.5	0.5	15	0.5	100	0.674925939	0.360565104
1049	0.05	8	0.5	0.5	17	0.5	100	0.672199268	0.355430714
1050	0.05	8	0.5	0.5	19	0.5	100	0.674168752	0.360536526

#	eta	max_depth	gamma	colsample_bytree	min_child_weight	subsample	nrounds	Accuracy	Kappa
1051	0.05	8	0.6	0.5	1	0.5	100	0.668109947	0.340374782
1052	0.05	8	0.6	0.5	3	0.5	100	0.671137109	0.347852391
1053	0.05	8	0.6	0.5	5	0.5	100	0.6710623	0.348690765
1054	0.05	8	0.6	0.5	7	0.5	100	0.671669653	0.350494589
1055	0.05	8	0.6	0.5	9	0.5	100	0.672010303	0.351974422
1056	0.05	8	0.6	0.5	11	0.5	100	0.671935493	0.35306242
1057	0.05	8	0.6	0.5	13	0.5	100	0.67125135	0.352328568
1058	0.05	8	0.6	0.5	15	0.5	100	0.675192685	0.36166588
1059	0.05	8	0.6	0.5	17	0.5	100	0.674283808	0.359974611
1060	0.05	8	0.6	0.5	19	0.5	100	0.674775975	0.36164457
1061	0.05	8	0.7	0.5	1	0.5	100	0.668713899	0.342532454
1062	0.05	8	0.7	0.5	3	0.5	100	0.671023947	0.347073914
1063	0.05	8	0.7	0.5	5	0.5	100	0.667654498	0.340443365
1064	0.05	8	0.7	0.5	7	0.5	100	0.669318368	0.345881672
1065	0.05	8	0.7	0.5	9	0.5	100	0.670645159	0.349112691
1066	0.05	8	0.7	0.5	11	0.5	100	0.671781265	0.352752629
1067	0.05	8	0.7	0.5	13	0.5	100	0.673600913	0.357653431
1068	0.05	8	0.7	0.5	15	0.5	100	0.674281011	0.358768399
1069	0.05	8	0.7	0.5	17	0.5	100	0.675304987	0.361569251
1070	0.05	8	0.7	0.5	19	0.5	100	0.677160617	0.366969189
1071	0.05	8	0.8	0.5	1	0.5	100	0.669625141	0.344439567
1072	0.05	8	0.8	0.5	3	0.5	100	0.671212696	0.347077598
1073	0.05	8	0.8	0.5	5	0.5	100	0.672350524	0.350570442
1074	0.05	8	0.8	0.5	7	0.5	100	0.669774592	0.34680585
1075	0.05	8	0.8	0.5	9	0.5	100	0.670871614	0.349866314
1076	0.05	8	0.8	0.5	11	0.5	100	0.671743904	0.352141679
1077	0.05	8	0.8	0.5	13	0.5	100	0.675418923	0.360666638
1078	0.05	8	0.8	0.5	15	0.5	100	0.675760952	0.362349521
1079	0.05	8	0.8	0.5	17	0.5	100	0.673299174	0.358926261
1080	0.05	8	0.8	0.5	19	0.5	100	0.675153557	0.362844778
1081	0.05	8	0.9	0.5	1	0.5	100	0.667881642	0.340507236
1082	0.05	8	0.9	0.5	3	0.5	100	0.668829343	0.34371404
1083	0.05	8	0.9	0.5	5	0.5	100	0.668562341	0.343043031
1084	0.05	8	0.9	0.5	7	0.5	100	0.669013486	0.344907155
1085	0.05	8	0.9	0.5	9	0.5	100	0.670909108	0.350054682
1086	0.05	8	0.9	0.5	11	0.5	100	0.673563506	0.356585178
1087	0.05	8	0.9	0.5	13	0.5	100	0.671972511	0.353676166
1088	0.05	8	0.9	0.5	15	0.5	100	0.675002687	0.361029038
1089	0.05	8	0.9	0.5	17	0.5	100	0.674357543	0.361162037
1090	0.05	8	0.9	0.5	19	0.5	100	0.674092305	0.360912454
1091	0.05	8	1	0.5	1	0.5	100	0.669662419	0.344124614
1092	0.05	8	1	0.5	3	0.5	100	0.66856191	0.342653479
1093	0.05	8	1	0.5	5	0.5	100	0.669621699	0.345434289
1094	0.05	8	1	0.5	7	0.5	100	0.673030492	0.353902218
1095	0.05	8	1	0.5	9	0.5	100	0.672727331	0.354305736
1096	0.05	8	1	0.5	11	0.5	100	0.671515296	0.352505265
1097	0.05	8	1	0.5	13	0.5	100	0.673978282	0.358184562
1098	0.05	8	1	0.5	15	0.5	100	0.672993992	0.35666754
1099	0.05	8	1	0.5	17	0.5	100	0.674736287	0.361581637
1100	0.05	8	1	0.5	19	0.5	100	0.675683172	0.363886329
1101	0.05	9	0	0.5	1	0.5	100	0.667957526	0.337662028
1102	0.05	9	0	0.5	3	0.5	100	0.66610069	0.333291716
1103	0.05	9	0	0.5	5	0.5	100	0.667767015	0.33913866
1104	0.05	9	0	0.5	7	0.5	100	0.671063806	0.347748117
1105	0.05	9	0	0.5	9	0.5	100	0.667879919	0.34147989
1106	0.05	9	0	0.5	11	0.5	100	0.671858615	0.351489738
1107	0.05	9	0	0.5	13	0.5	100	0.668598369	0.345829758
1108	0.05	9	0	0.5	15	0.5	100	0.676252258	0.362097144
1109	0.05	9	0	0.5	17	0.5	100	0.673865721	0.357419244
1110	0.05	9	0	0.5	19	0.5	100	0.672615203	0.357056874
1111	0.05	9	0.1	0.5	1	0.5	100	0.669661688	0.340398295
1112	0.05	9	0.1	0.5	3	0.5	100	0.668600609	0.339049894
1113	0.05	9	0.1	0.5	5	0.5	100	0.669586404	0.34232884
1114	0.05	9	0.1	0.5	7	0.5	100	0.667464589	0.339514433
1115	0.05	9	0.1	0.5	9	0.5	100	0.671518526	0.349403904
1116	0.05	9	0.1	0.5	11	0.5	100	0.668716482	0.344341068
1117	0.05	9	0.1	0.5	13	0.5	100	0.67337321	0.355608506
1118	0.05	9	0.1	0.5	15	0.5	100	0.67329801	0.356257189
1119	0.05	9	0.1	0.5	17	0.5	100	0.673942167	0.358780317
1120	0.05	9	0.1	0.5	19	0.5	100	0.672235555	0.355672222
1121	0.05	9	0.2	0.5	1	0.5	100	0.667160266	0.334695574
1122	0.05	9	0.2	0.5	3	0.5	100	0.665078609	0.332422773
1123	0.05	9	0.2	0.5	5	0.5	100	0.667465963	0.338055079
1124	0.05	9	0.2	0.5	7	0.5	100	0.667540216	0.340162129
1125	0.05	9	0.2	0.5	9	0.5	100	0.67030382	0.347530128
1126	0.05	9	0.2	0.5	11	0.5	100	0.670229182	0.348856537
1127	0.05	9	0.2	0.5	13	0.5	100	0.669849792	0.348384245
1128	0.05	9	0.2	0.5	15	0.5	100	0.675458224	0.360276916
1129	0.05	9	0.2	0.5	17	0.5	100	0.67394066	0.358329367
1130	0.05	9	0.2	0.5	19	0.5	100	0.676328705	0.363767704
1131	0.05	9	0.3	0.5	1	0.5	100	0.664320343	0.329040645
1132	0.05	9	0.3	0.5	3	0.5	100	0.666591265	0.335279003
1133	0.05	9	0.3	0.5	5	0.5	100	0.667956538	0.339810161
1134	0.05	9	0.3	0.5	7	0.5	100	0.669774505	0.345415499
1135	0.05	9	0.3	0.5	9	0.5	100	0.672579045	0.351622358
1136	0.05	9	0.3	0.5	11	0.5	100	0.671894987	0.351495133
1137	0.05	9	0.3	0.5	13	0.5	100	0.67155507	0.352441297
1138	0.05	9	0.3	0.5	15	0.5	100	0.671364471	0.352056011
1139	0.05	9	0.3	0.5	17	0.5	100	0.672236114	0.355437124
1140	0.05	9	0.3	0.5	19	0.5	100	0.673905406	0.358824016
1141	0.05	9	0.4	0.5	1	0.5	100	0.665532379	0.33226215
1142	0.05	9	0.4	0.5	3	0.5	100	0.667160265	0.335973545
1143	0.05	9	0.4	0.5	5	0.5	100	0.66822255	0.339761912
1144	0.05	9	0.4	0.5	7	0.5	100	0.668484946	0.341554611
1145	0.05	9	0.4	0.5	9	0.5	100	0.669130222	0.344340184
1146	0.05	9	0.4	0.5	11	0.5	100	0.669394123	0.346060462
1147	0.05	9	0.4	0.5	13	0.5	100	0.671933428	0.351875572
1148	0.05	9	0.4	0.5	15	0.5	100	0.671667374	0.352791418
1149	0.05	9	0.4	0.5	17	0.5	100	0.672389479	0.354690674
1150	0.05	9	0.4	0.5	19	0.5	100	0.673298314	0.358234318
1151	0.05	9	0.5	0.5	1	0.5	100	0.666288837	0.333760584
1152	0.05	9	0.5	0.5	3	0.5	100	0.667994762	0.338427157
1153	0.05	9	0.5	0.5	5	0.5	100	0.66954848	0.343344626
1154	0.05	9	0.5	0.5	7	0.5	100	0.669775065	0.344411424
1155	0.05	9	0.5	0.5	9	0.5	100	0.670040346	0.346831193
1156	0.05	9	0.5	0.5	11	0.5	100	0.669244548	0.34588787
1157	0.05	9	0.5	0.5	13	0.5	100	0.673374069	0.354977057
1158	0.05	9	0.5	0.5	15	0.5	100	0.673752601	0.357414942
1159	0.05	9	0.5	0.5	17	0.5	100	0.674055243	0.358363531
1160	0.05	9	0.5	0.5	19	0.5	100	0.674056362	0.359229566
1161	0.05	9	0.6	0.5	1	0.5	100	0.666893993	0.334254621
1162	0.05	9	0.6	0.5	3	0.5	100	0.666933164	0.336723415
1163	0.05	9	0.6	0.5	5	0.5	100	0.666932302	0.337651287
1164	0.05	9	0.6	0.5	7	0.5	100	0.668865028	0.343221238
1165	0.05	9	0.6	0.5	9	0.5	100	0.67166905	0.350182747
1166	0.05	9	0.6	0.5	11	0.5	100	0.67205012	0.351762552
1167	0.05	9	0.6	0.5	13	0.5	100	0.674283507	0.357197309
1168	0.05	9	0.6	0.5	15	0.5	100	0.671969154	0.353773546
1169	0.05	9	0.6	0.5	17	0.5	100	0.673600741	0.358070554
1170	0.05	9	0.6	0.5	19	0.5	100	0.673864386	0.358980982
1171	0.05	9	0.7	0.5	1	0.5	100	0.66549476	0.332212507
1172	0.05	9	0.7	0.5	3	0.5	100	0.666819356	0.335601764
1173	0.05	9	0.7	0.5	5	0.5	100	0.669624799	0.343377827
1174	0.05	9	0.7	0.5	7	0.5	100	0.668900884	0.342760386
1175	0.05	9	0.7	0.5	9	0.5	100	0.667350089	0.340594755
1176	0.05	9	0.7	0.5	11	0.5	100	0.671969927	0.35212015
1177	0.05	9	0.7	0.5	13	0.5	100	0.671363996	0.351295486
1178	0.05	9	0.7	0.5	15	0.5	100	0.672538456	0.354797096
1179	0.05	9	0.7	0.5	17	0.5	100	0.673372393	0.358141343
1180	0.05	9	0.7	0.5	19	0.5	100	0.674205167	0.360307875
1181	0.05	9	0.8	0.5	1	0.5	100	0.668866403	0.339218311
1182	0.05	9	0.8	0.5	3	0.5	100	0.669848412	0.342017346
1183	0.05	9	0.8	0.5	5	0.5	100	0.668677571	0.342275397
1184	0.05	9	0.8	0.5	7	0.5	100	0.669508666	0.344524901
1185	0.05	9	0.8	0.5	9	0.5	100	0.669622948	0.345838606
1186	0.05	9	0.8	0.5	11	0.5	100	0.670001522	0.347838341
1187	0.05	9	0.8	0.5	13	0.5	100	0.671669136	0.352159976
1188	0.05	9	0.8	0.5	15	0.5	100	0.67019126	0.350295506
1189	0.05	9	0.8	0.5	17	0.5	100	0.675798401	0.362999665
1190	0.05	9	0.8	0.5	19	0.5	100	0.676403386	0.364351339
1191	0.05	9	0.9	0.5	1	0.5	100	0.66784329	0.3367706
1192	0.05	9	0.9	0.5	3	0.5	100	0.66772888	0.337898806
1193	0.05	9	0.9	0.5	5	0.5	100	0.667428344	0.339214078
1194	0.05	9	0.9	0.5	7	0.5	100	0.671251953	0.347692569
1195	0.05	9	0.9	0.5	9	0.5	100	0.670988178	0.349322987
1196	0.05	9	0.9	0.5	11	0.5	100	0.671174602	0.350695534
1197	0.05	9	0.9	0.5	13	0.5	100	0.672540135	0.354489368
1198	0.05	9	0.9	0.5	15	0.5	100	0.672159064	0.354346324
1199	0.05	9	0.9	0.5	17	0.5	100	0.672842175	0.357065528
1200	0.05	9	0.9	0.5	19	0.5	100	0.67530589	0.362002399

#	eta	max_depth	gamma	colsample_bytree	min_child_weight	subsample	nrounds	Accuracy	Kappa
1201	0.05	9	1	0.5	1	0.5	100	0.666325726	0.334978421
1202	0.05	9	1	0.5	3	0.5	100	0.670988048	0.344232335
1203	0.05	9	1	0.5	5	0.5	100	0.668409705	0.341107994
1204	0.05	9	1	0.5	7	0.5	100	0.668791767	0.34329434
1205	0.05	9	1	0.5	9	0.5	100	0.668788883	0.343746374
1206	0.05	9	1	0.5	11	0.5	100	0.669585155	0.34766858
1207	0.05	9	1	0.5	13	0.5	100	0.671480215	0.352287461
1208	0.05	9	1	0.5	15	0.5	100	0.67348801	0.356543618
1209	0.05	9	1	0.5	17	0.5	100	0.675646498	0.362635812
1210	0.05	9	1	0.5	19	0.5	100	0.675114041	0.361882417
1211	0.05	10	0	0.5	1	0.5	100	0.665380694	0.329078629
1212	0.05	10	0	0.5	3	0.5	100	0.662389212	0.324841902
1213	0.05	10	0	0.5	5	0.5	100	0.665193323	0.332226721
1214	0.05	10	0	0.5	7	0.5	100	0.666820218	0.33663891
1215	0.05	10	0	0.5	9	0.5	100	0.669734732	0.344268851
1216	0.05	10	0	0.5	11	0.5	100	0.669055068	0.344505674
1217	0.05	10	0	0.5	13	0.5	100	0.670227244	0.348588477
1218	0.05	10	0	0.5	15	0.5	100	0.672047365	0.353062033
1219	0.05	10	0	0.5	17	0.5	100	0.672009572	0.354616458
1220	0.05	10	0	0.5	19	0.5	100	0.674623125	0.360542832
1221	0.05	10	0.1	0.5	1	0.5	100	0.662918012	0.323924719
1222	0.05	10	0.1	0.5	3	0.5	100	0.66765368	0.335390773
1223	0.05	10	0.1	0.5	5	0.5	100	0.667768606	0.337087449
1224	0.05	10	0.1	0.5	7	0.5	100	0.664507412	0.332028207
1225	0.05	10	0.1	0.5	9	0.5	100	0.670228578	0.346059508
1226	0.05	10	0.1	0.5	11	0.5	100	0.67068235	0.34761195
1227	0.05	10	0.1	0.5	13	0.5	100	0.671518652	0.350514015
1228	0.05	10	0.1	0.5	15	0.5	100	0.672502426	0.353984645
1229	0.05	10	0.1	0.5	17	0.5	100	0.672426714	0.355058659
1230	0.05	10	0.1	0.5	19	0.5	100	0.672691261	0.356025052
1231	0.05	10	0.2	0.5	1	0.5	100	0.666554463	0.332313283
1232	0.05	10	0.2	0.5	3	0.5	100	0.665607578	0.330960212
1233	0.05	10	0.2	0.5	5	0.5	100	0.665418659	0.331905211
1234	0.05	10	0.2	0.5	7	0.5	100	0.669736629	0.342850304
1235	0.05	10	0.2	0.5	9	0.5	100	0.66833481	0.341616593
1236	0.05	10	0.2	0.5	11	0.5	100	0.670230085	0.347099367
1237	0.05	10	0.2	0.5	13	0.5	100	0.670910614	0.350162084
1238	0.05	10	0.2	0.5	15	0.5	100	0.673146411	0.355246596
1239	0.05	10	0.2	0.5	17	0.5	100	0.673184333	0.356093746
1240	0.05	10	0.2	0.5	19	0.5	100	0.674281699	0.360216449
1241	0.05	10	0.3	0.5	1	0.5	100	0.661820859	0.321212917
1242	0.05	10	0.3	0.5	3	0.5	100	0.666402215	0.333022704
1243	0.05	10	0.3	0.5	5	0.5	100	0.667235806	0.336649412
1244	0.05	10	0.3	0.5	7	0.5	100	0.666212908	0.335933083
1245	0.05	10	0.3	0.5	9	0.5	100	0.669131514	0.343163815
1246	0.05	10	0.3	0.5	11	0.5	100	0.668978147	0.343851258
1247	0.05	10	0.3	0.5	13	0.5	100	0.671592303	0.350886925
1248	0.05	10	0.3	0.5	15	0.5	100	0.6712891	0.351696665
1249	0.05	10	0.3	0.5	17	0.5	100	0.675229228	0.360869983
1250	0.05	10	0.3	0.5	19	0.5	100	0.674018828	0.358542102
1251	0.05	10	0.4	0.5	1	0.5	100	0.663791505	0.325739526
1252	0.05	10	0.4	0.5	3	0.5	100	0.667881641	0.336181423
1253	0.05	10	0.4	0.5	5	0.5	100	0.666137279	0.334247639
1254	0.05	10	0.4	0.5	7	0.5	100	0.667086962	0.337362959
1255	0.05	10	0.4	0.5	9	0.5	100	0.668749454	0.342671924
1256	0.05	10	0.4	0.5	11	0.5	100	0.669055454	0.34420355
1257	0.05	10	0.4	0.5	13	0.5	100	0.670191346	0.348380869
1258	0.05	10	0.4	0.5	15	0.5	100	0.672047494	0.352995129
1259	0.05	10	0.4	0.5	17	0.5	100	0.674434505	0.358228643
1260	0.05	10	0.4	0.5	19	0.5	100	0.67542013	0.362200576
1261	0.05	10	0.5	0.5	1	0.5	100	0.661935702	0.321408967
1262	0.05	10	0.5	0.5	3	0.5	100	0.665305064	0.330367348
1263	0.05	10	0.5	0.5	5	0.5	100	0.667613734	0.336891173
1264	0.05	10	0.5	0.5	7	0.5	100	0.668487358	0.340053552
1265	0.05	10	0.5	0.5	9	0.5	100	0.66795895	0.341002581
1266	0.05	10	0.5	0.5	11	0.5	100	0.669660008	0.345218816
1267	0.05	10	0.5	0.5	13	0.5	100	0.669433985	0.346370992
1268	0.05	10	0.5	0.5	15	0.5	100	0.67079788	0.35052705
1269	0.05	10	0.5	0.5	17	0.5	100	0.672841788	0.356287972
1270	0.05	10	0.5	0.5	19	0.5	100	0.674699785	0.360718358
1271	0.05	10	0.6	0.5	1	0.5	100	0.665757587	0.3289909
1272	0.05	10	0.6	0.5	3	0.5	100	0.668677397	0.337282092
1273	0.05	10	0.6	0.5	5	0.5	100	0.669016242	0.339436953
1274	0.05	10	0.6	0.5	7	0.5	100	0.669963858	0.342915908
1275	0.05	10	0.6	0.5	9	0.5	100	0.669091437	0.342744129
1276	0.05	10	0.6	0.5	11	0.5	100	0.668297492	0.3431683
1277	0.05	10	0.6	0.5	13	0.5	100	0.670001565	0.347574599
1278	0.05	10	0.6	0.5	15	0.5	100	0.671706241	0.352501113
1279	0.05	10	0.6	0.5	17	0.5	100	0.673336236	0.356781761
1280	0.05	10	0.6	0.5	19	0.5	100	0.672919137	0.35696699
1281	0.05	10	0.7	0.5	1	0.5	100	0.664509093	0.32730594
1282	0.05	10	0.7	0.5	3	0.5	100	0.665949606	0.332010938
1283	0.05	10	0.7	0.5	5	0.5	100	0.666819313	0.335685191
1284	0.05	10	0.7	0.5	7	0.5	100	0.669848629	0.343460517
1285	0.05	10	0.7	0.5	9	0.5	100	0.667274031	0.339290901
1286	0.05	10	0.7	0.5	11	0.5	100	0.668978751	0.345288011
1287	0.05	10	0.7	0.5	13	0.5	100	0.668904886	0.34592752
1288	0.05	10	0.7	0.5	15	0.5	100	0.673487361	0.355830476
1289	0.05	10	0.7	0.5	17	0.5	100	0.673790134	0.358035676
1290	0.05	10	0.7	0.5	19	0.5	100	0.67625157	0.363036928
1291	0.05	10	0.8	0.5	1	0.5	100	0.669357408	0.337024324
1292	0.05	10	0.8	0.5	3	0.5	100	0.665759565	0.331120526
1293	0.05	10	0.8	0.5	5	0.5	100	0.667804936	0.338253251
1294	0.05	10	0.8	0.5	7	0.5	100	0.665345398	0.334182217
1295	0.05	10	0.8	0.5	9	0.5	100	0.669280961	0.344029177
1296	0.05	10	0.8	0.5	11	0.5	100	0.671858444	0.350647688
1297	0.05	10	0.8	0.5	13	0.5	100	0.67193334	0.352243281
1298	0.05	10	0.8	0.5	15	0.5	100	0.672198494	0.353280107
1299	0.05	10	0.8	0.5	17	0.5	100	0.67269109	0.355404072
1300	0.05	10	0.8	0.5	19	0.5	100	0.67409183	0.35918416
1301	0.05	10	0.9	0.5	1	0.5	100	0.666784016	0.332753999
1302	0.05	10	0.9	0.5	3	0.5	100	0.666478361	0.334090985
1303	0.05	10	0.9	0.5	5	0.5	100	0.66678109	0.335955321
1304	0.05	10	0.9	0.5	7	0.5	100	0.66769117	0.338942505
1305	0.05	10	0.9	0.5	9	0.5	100	0.669319099	0.343753582
1306	0.05	10	0.9	0.5	11	0.5	100	0.670267749	0.346875678
1307	0.05	10	0.9	0.5	13	0.5	100	0.674319534	0.356895605
1308	0.05	10	0.9	0.5	15	0.5	100	0.674472254	0.358625746
1309	0.05	10	0.9	0.5	17	0.5	100	0.673562776	0.357037191
1310	0.05	10	0.9	0.5	19	0.5	100	0.673637672	0.358666417
1311	0.05	10	1	0.5	1	0.5	100	0.666860076	0.333129498
1312	0.05	10	1	0.5	3	0.5	100	0.668864424	0.338246609
1313	0.05	10	1	0.5	5	0.5	100	0.665419517	0.332698777
1314	0.05	10	1	0.5	7	0.5	100	0.668069658	0.340152049
1315	0.05	10	1	0.5	9	0.5	100	0.668789143	0.343233904
1316	0.05	10	1	0.5	11	0.5	100	0.669358658	0.345803131
1317	0.05	10	1	0.5	13	0.5	100	0.670532556	0.34922179
1318	0.05	10	1	0.5	15	0.5	100	0.669889393	0.348984865
1319	0.05	10	1	0.5	17	0.5	100	0.674850613	0.359564194
1320	0.05	10	1	0.5	19	0.5	100	0.675458138	0.362023353
1321	0.05	5	0	0.5	1	0.5	150	0.675948108	0.364487321
1322	0.05	5	0	0.5	3	0.5	150	0.675911866	0.36577218
1323	0.05	5	0	0.5	5	0.5	150	0.678145421	0.369527626
1324	0.05	5	0	0.5	7	0.5	150	0.673145249	0.359460878
1325	0.05	5	0	0.5	9	0.5	150	0.677805676	0.368959206
1326	0.05	5	0	0.5	11	0.5	150	0.675038973	0.363850264
1327	0.05	5	0	0.5	13	0.5	150	0.673487276	0.362023349
1328	0.05	5	0	0.5	15	0.5	150	0.677160317	0.368454932
1329	0.05	5	0	0.5	17	0.5	150	0.678677665	0.37218041
1330	0.05	5	0	0.5	19	0.5	150	0.677351303	0.369215637
1331	0.05	5	0.1	0.5	1	0.5	150	0.677994126	0.369005729
1332	0.05	5	0.1	0.5	3	0.5	150	0.677501872	0.367876622
1333	0.05	5	0.1	0.5	5	0.5	150	0.67458546	0.362239547
1334	0.05	5	0.1	0.5	7	0.5	150	0.674660056	0.363397894
1335	0.05	5	0.1	0.5	9	0.5	150	0.677385997	0.36865331
1336	0.05	5	0.1	0.5	11	0.5	150	0.674508283	0.363630969
1337	0.05	5	0.1	0.5	13	0.5	150	0.677236547	0.368913362
1338	0.05	5	0.1	0.5	15	0.5	150	0.674810711	0.364332169
1339	0.05	5	0.1	0.5	17	0.5	150	0.677538028	0.369896759
1340	0.05	5	0.1	0.5	19	0.5	150	0.67901836	0.372541031
1341	0.05	5	0.2	0.5	1	0.5	150	0.671667759	0.356501089
1342	0.05	5	0.2	0.5	3	0.5	150	0.676023867	0.365164537
1343	0.05	5	0.2	0.5	5	0.5	150	0.674621274	0.362699624
1344	0.05	5	0.2	0.5	7	0.5	150	0.676062432	0.365807968
1345	0.05	5	0.2	0.5	9	0.5	150	0.675647359	0.365540987
1346	0.05	5	0.2	0.5	11	0.5	150	0.677198066	0.368719217
1347	0.05	5	0.2	0.5	13	0.5	150	0.678220579	0.370392941
1348	0.05	5	0.2	0.5	15	0.5	150	0.676630358	0.367860005
1349	0.05	5	0.2	0.5	17	0.5	150	0.675645809	0.365424777
1350	0.05	5	0.2	0.5	19	0.5	150	0.67693257	0.368932931

#	eta	max_depth	gamma	colsample_bytree	min_child_weight	subsample	nrounds	Accuracy	Kappa
1351	0.05	5	0.3	0.5	1	0.5	150	0.676669268	0.366027655
1352	0.05	5	0.3	0.5	3	0.5	150	0.676741712	0.366377133
1353	0.05	5	0.3	0.5	5	0.5	150	0.677729573	0.368218391
1354	0.05	5	0.3	0.5	7	0.5	150	0.67484975	0.363171213
1355	0.05	5	0.3	0.5	9	0.5	150	0.676062906	0.365832892
1356	0.05	5	0.3	0.5	11	0.5	150	0.67541858	0.365254115
1357	0.05	5	0.3	0.5	13	0.5	150	0.675683389	0.365808897
1358	0.05	5	0.3	0.5	15	0.5	150	0.676590971	0.367728746
1359	0.05	5	0.3	0.5	17	0.5	150	0.675418106	0.36535842
1360	0.05	5	0.3	0.5	19	0.5	150	0.676250581	0.367344561
1361	0.05	5	0.4	0.5	1	0.5	150	0.675492185	0.363738161
1362	0.05	5	0.4	0.5	3	0.5	150	0.67564654	0.363637355
1363	0.05	5	0.4	0.5	5	0.5	150	0.676441135	0.366415192
1364	0.05	5	0.4	0.5	7	0.5	150	0.676402741	0.366206378
1365	0.05	5	0.4	0.5	9	0.5	150	0.67693399	0.367935888
1366	0.05	5	0.4	0.5	11	0.5	150	0.67640188	0.366739258
1367	0.05	5	0.4	0.5	13	0.5	150	0.678334302	0.370719533
1368	0.05	5	0.4	0.5	15	0.5	150	0.676176069	0.366831522
1369	0.05	5	0.4	0.5	17	0.5	150	0.67454711	0.363665451
1370	0.05	5	0.4	0.5	19	0.5	150	0.677274426	0.36867269
1371	0.05	5	0.5	0.5	1	0.5	150	0.676175466	0.36512459
1372	0.05	5	0.5	0.5	3	0.5	150	0.676402525	0.366317859
1373	0.05	5	0.5	0.5	5	0.5	150	0.674887156	0.363035415
1374	0.05	5	0.5	0.5	7	0.5	150	0.676669529	0.367121592
1375	0.05	5	0.5	0.5	9	0.5	150	0.676215627	0.365862964
1376	0.05	5	0.5	0.5	11	0.5	150	0.67765274	0.369883958
1377	0.05	5	0.5	0.5	13	0.5	150	0.676556709	0.367493634
1378	0.05	5	0.5	0.5	15	0.5	150	0.674888061	0.364320679
1379	0.05	5	0.5	0.5	17	0.5	150	0.677690749	0.369828066
1380	0.05	5	0.5	0.5	19	0.5	150	0.677236074	0.368510406
1381	0.05	5	0.6	0.5	1	0.5	150	0.676933044	0.36699114
1382	0.05	5	0.6	0.5	3	0.5	150	0.674507851	0.361894818
1383	0.05	5	0.6	0.5	5	0.5	150	0.674281613	0.362541489
1384	0.05	5	0.6	0.5	7	0.5	150	0.676855738	0.36758637
1385	0.05	5	0.6	0.5	9	0.5	150	0.678562607	0.370508528
1386	0.05	5	0.6	0.5	11	0.5	150	0.675380614	0.364872791
1387	0.05	5	0.6	0.5	13	0.5	150	0.67545633	0.365636352
1388	0.05	5	0.6	0.5	15	0.5	150	0.677614303	0.370073234
1389	0.05	5	0.6	0.5	17	0.5	150	0.678448971	0.37121422
1390	0.05	5	0.6	0.5	19	0.5	150	0.677311359	0.36886906
1391	0.05	5	0.7	0.5	1	0.5	150	0.677804731	0.368618859
1392	0.05	5	0.7	0.5	3	0.5	150	0.673144689	0.359748276
1393	0.05	5	0.7	0.5	5	0.5	150	0.676024555	0.365762479
1394	0.05	5	0.7	0.5	7	0.5	150	0.676248856	0.365920679
1395	0.05	5	0.7	0.5	9	0.5	150	0.674924133	0.36340292
1396	0.05	5	0.7	0.5	11	0.5	150	0.676932785	0.367319544
1397	0.05	5	0.7	0.5	13	0.5	150	0.676251656	0.366839365
1398	0.05	5	0.7	0.5	15	0.5	150	0.676252086	0.367573764
1399	0.05	5	0.7	0.5	17	0.5	150	0.677274297	0.369280745
1400	0.05	5	0.7	0.5	19	0.5	150	0.677692814	0.369788254
1401	0.05	5	0.8	0.5	1	0.5	150	0.675797669	0.364713592
1402	0.05	5	0.8	0.5	3	0.5	150	0.675380313	0.363983769
1403	0.05	5	0.8	0.5	5	0.5	150	0.676098977	0.366010436
1404	0.05	5	0.8	0.5	7	0.5	150	0.674355692	0.362786339
1405	0.05	5	0.8	0.5	9	0.5	150	0.675759835	0.365375939
1406	0.05	5	0.8	0.5	11	0.5	150	0.675075474	0.363778312
1407	0.05	5	0.8	0.5	13	0.5	150	0.676517281	0.367866449
1408	0.05	5	0.8	0.5	15	0.5	150	0.677843298	0.370390303
1409	0.05	5	0.8	0.5	17	0.5	150	0.677653344	0.370068823
1410	0.05	5	0.8	0.5	19	0.5	150	0.676896069	0.368452584
1411	0.05	5	0.9	0.5	1	0.5	150	0.672726515	0.35932498
1412	0.05	5	0.9	0.5	3	0.5	150	0.675644517	0.364787553
1413	0.05	5	0.9	0.5	5	0.5	150	0.678826037	0.371315401
1414	0.05	5	0.9	0.5	7	0.5	150	0.674206501	0.362123805
1415	0.05	5	0.9	0.5	9	0.5	150	0.675758283	0.365564512
1416	0.05	5	0.9	0.5	11	0.5	150	0.67545633	0.36515961
1417	0.05	5	0.9	0.5	13	0.5	150	0.675531656	0.365895631
1418	0.05	5	0.9	0.5	15	0.5	150	0.676780926	0.36821993
1419	0.05	5	0.9	0.5	17	0.5	150	0.680494041	0.375664542
1420	0.05	5	0.9	0.5	19	0.5	150	0.677614347	0.36991197
1421	0.05	5	1	0.5	1	0.5	150	0.676214251	0.365973184
1422	0.05	5	1	0.5	3	0.5	150	0.67591191	0.364679662
1423	0.05	5	1	0.5	5	0.5	150	0.676705899	0.366989618
1424	0.05	5	1	0.5	7	0.5	150	0.675722944	0.364731175
1425	0.05	5	1	0.5	9	0.5	150	0.676251396	0.367118662
1426	0.05	5	1	0.5	11	0.5	150	0.677122997	0.368400258
1427	0.05	5	1	0.5	13	0.5	150	0.676780883	0.367956182
1428	0.05	5	1	0.5	15	0.5	150	0.677048187	0.368708104
1429	0.05	5	1	0.5	17	0.5	150	0.677387847	0.369158987
1430	0.05	5	1	0.5	19	0.5	150	0.678827716	0.372601836
1431	0.05	6	0	0.5	1	0.5	150	0.672578013	0.353792494
1432	0.05	6	0	0.5	3	0.5	150	0.673107152	0.354585018
1433	0.05	6	0	0.5	5	0.5	150	0.671402693	0.352309284
1434	0.05	6	0	0.5	7	0.5	150	0.669813203	0.349013813
1435	0.05	6	0	0.5	9	0.5	150	0.672463386	0.355510887
1436	0.05	6	0	0.5	11	0.5	150	0.672767923	0.355760287
1437	0.05	6	0	0.5	13	0.5	150	0.673109178	0.356780921
1438	0.05	6	0	0.5	15	0.5	150	0.674698452	0.360974182
1439	0.05	6	0	0.5	17	0.5	150	0.673033162	0.358584146
1440	0.05	6	0	0.5	19	0.5	150	0.674092219	0.359719905
1441	0.05	6	0.1	0.5	1	0.5	150	0.67360074	0.355361846
1442	0.05	6	0.1	0.5	3	0.5	150	0.672501782	0.353559333
1443	0.05	6	0.1	0.5	5	0.5	150	0.673146021	0.355578195
1444	0.05	6	0.1	0.5	7	0.5	150	0.670833346	0.35137335
1445	0.05	6	0.1	0.5	9	0.5	150	0.671817854	0.353255406
1446	0.05	6	0.1	0.5	11	0.5	150	0.67307048	0.357687802
1447	0.05	6	0.1	0.5	13	0.5	150	0.674659109	0.360404455
1448	0.05	6	0.1	0.5	15	0.5	150	0.675189928	0.361689167
1449	0.05	6	0.1	0.5	17	0.5	150	0.67644148	0.364953456
1450	0.05	6	0.1	0.5	19	0.5	150	0.675001784	0.362224075
1451	0.05	6	0.2	0.5	1	0.5	150	0.672577322	0.353337697
1452	0.05	6	0.2	0.5	3	0.5	150	0.672236672	0.353093114
1453	0.05	6	0.2	0.5	5	0.5	150	0.673675249	0.356852194
1454	0.05	6	0.2	0.5	7	0.5	150	0.6720849	0.354075059
1455	0.05	6	0.2	0.5	9	0.5	150	0.673865202	0.358160198
1456	0.05	6	0.2	0.5	11	0.5	150	0.672389523	0.355533534
1457	0.05	6	0.2	0.5	13	0.5	150	0.673221522	0.357221098
1458	0.05	6	0.2	0.5	15	0.5	150	0.674318974	0.359816731
1459	0.05	6	0.2	0.5	17	0.5	150	0.675418578	0.362557794
1460	0.05	6	0.2	0.5	19	0.5	150	0.673941392	0.359801958
1461	0.05	6	0.3	0.5	1	0.5	150	0.675040351	0.358182952
1462	0.05	6	0.3	0.5	3	0.5	150	0.673747949	0.356175717
1463	0.05	6	0.3	0.5	5	0.5	150	0.672007247	0.353229018
1464	0.05	6	0.3	0.5	7	0.5	150	0.671553605	0.35279779
1465	0.05	6	0.3	0.5	9	0.5	150	0.671441432	0.353150655
1466	0.05	6	0.3	0.5	11	0.5	150	0.67397828	0.357878511
1467	0.05	6	0.3	0.5	13	0.5	150	0.67185612	0.355080847
1468	0.05	6	0.3	0.5	15	0.5	150	0.676592995	0.36466147
1469	0.05	6	0.3	0.5	17	0.5	150	0.674584299	0.361003521
1470	0.05	6	0.3	0.5	19	0.5	150	0.674431706	0.361272728
1471	0.05	6	0.4	0.5	1	0.5	150	0.672389177	0.352946605
1472	0.05	6	0.4	0.5	3	0.5	150	0.672010606	0.352847937
1473	0.05	6	0.4	0.5	5	0.5	150	0.672313677	0.354061509
1474	0.05	6	0.4	0.5	7	0.5	150	0.673677273	0.357051461
1475	0.05	6	0.4	0.5	9	0.5	150	0.674434592	0.359176329
1476	0.05	6	0.4	0.5	11	0.5	150	0.674469715	0.359467756
1477	0.05	6	0.4	0.5	13	0.5	150	0.673903643	0.359274384
1478	0.05	6	0.4	0.5	15	0.5	150	0.675494466	0.361903698
1479	0.05	6	0.4	0.5	17	0.5	150	0.676631993	0.365171351
1480	0.05	6	0.4	0.5	19	0.5	150	0.676365636	0.364831027
1481	0.05	6	0.5	0.5	1	0.5	150	0.670378932	0.34930657
1482	0.05	6	0.5	0.5	3	0.5	150	0.672426022	0.3528375
1483	0.05	6	0.5	0.5	5	0.5	150	0.673333608	0.356499652
1484	0.05	6	0.5	0.5	7	0.5	150	0.6717068	0.352741143
1485	0.05	6	0.5	0.5	9	0.5	150	0.67166819	0.353073027
1486	0.05	6	0.5	0.5	11	0.5	150	0.671745583	0.35418124
1487	0.05	6	0.5	0.5	13	0.5	150	0.674433731	0.360159376
1488	0.05	6	0.5	0.5	15	0.5	150	0.674130914	0.360016828
1489	0.05	6	0.5	0.5	17	0.5	150	0.676061186	0.364271028
1490	0.05	6	0.5	0.5	19	0.5	150	0.673221609	0.358361048
1491	0.05	6	0.6	0.5	1	0.5	150	0.672350137	0.353198133
1492	0.05	6	0.6	0.5	3	0.5	150	0.672804596	0.355037801
1493	0.05	6	0.6	0.5	5	0.5	150	0.671026273	0.351641861
1494	0.05	6	0.6	0.5	7	0.5	150	0.671023518	0.351699623
1495	0.05	6	0.6	0.5	9	0.5	150	0.672122993	0.354451888
1496	0.05	6	0.6	0.5	11	0.5	150	0.674205425	0.359440377
1497	0.05	6	0.6	0.5	13	0.5	150	0.676176372	0.363481621
1498	0.05	6	0.6	0.5	15	0.5	150	0.67462334	0.360874069
1499	0.05	6	0.6	0.5	17	0.5	150	0.676857974	0.365761163
1500	0.05	6	0.6	0.5	19	0.5	150	0.675077584	0.361859803

#	eta	max_depth	gamma	colsample_bytree	min_child_weight	subsample	nrounds	Accuracy	Kappa
1501	0.05	6	0.7	0.5	1	0.5	150	0.672085199	0.352203172
1502	0.05	6	0.7	0.5	3	0.5	150	0.675078014	0.358924269
1503	0.05	6	0.7	0.5	5	0.5	150	0.672577539	0.354741818
1504	0.05	6	0.7	0.5	7	0.5	150	0.672994163	0.355425312
1505	0.05	6	0.7	0.5	9	0.5	150	0.671894814	0.353601631
1506	0.05	6	0.7	0.5	11	0.5	150	0.673751868	0.358417506
1507	0.05	6	0.7	0.5	13	0.5	150	0.673335804	0.357676647
1508	0.05	6	0.7	0.5	15	0.5	150	0.673676111	0.358586685
1509	0.05	6	0.7	0.5	17	0.5	150	0.675116626	0.362048096
1510	0.05	6	0.7	0.5	19	0.5	150	0.675078359	0.361607596
1511	0.05	6	0.8	0.5	1	0.5	150	0.67022789	0.348421235
1512	0.05	6	0.8	0.5	3	0.5	150	0.673447762	0.355662844
1513	0.05	6	0.8	0.5	5	0.5	150	0.672046977	0.353546092
1514	0.05	6	0.8	0.5	7	0.5	150	0.672577324	0.354529219
1515	0.05	6	0.8	0.5	9	0.5	150	0.672237018	0.354188856
1516	0.05	6	0.8	0.5	11	0.5	150	0.673825214	0.35880727
1517	0.05	6	0.8	0.5	13	0.5	150	0.674319707	0.359976899
1518	0.05	6	0.8	0.5	15	0.5	150	0.672920344	0.357248264
1519	0.05	6	0.8	0.5	17	0.5	150	0.674926499	0.361689558
1520	0.05	6	0.8	0.5	19	0.5	150	0.674737063	0.361381593
1521	0.05	6	0.9	0.5	1	0.5	150	0.671327753	0.350523959
1522	0.05	6	0.9	0.5	3	0.5	150	0.674320565	0.358221665
1523	0.05	6	0.9	0.5	5	0.5	150	0.672463515	0.354323494
1524	0.05	6	0.9	0.5	7	0.5	150	0.669547363	0.34908961
1525	0.05	6	0.9	0.5	9	0.5	150	0.671327925	0.352861671
1526	0.05	6	0.9	0.5	11	0.5	150	0.673335847	0.357301896
1527	0.05	6	0.9	0.5	13	0.5	150	0.675003635	0.361857801
1528	0.05	6	0.9	0.5	15	0.5	150	0.675305417	0.362442932
1529	0.05	6	0.9	0.5	17	0.5	150	0.674813163	0.361143417
1530	0.05	6	0.9	0.5	19	0.5	150	0.675834387	0.363865807
1531	0.05	6	1	0.5	1	0.5	150	0.672085371	0.353292412
1532	0.05	6	1	0.5	3	0.5	150	0.672692296	0.354002179
1533	0.05	6	1	0.5	5	0.5	150	0.6734104	0.356657592
1534	0.05	6	1	0.5	7	0.5	150	0.67235104	0.354853058
1535	0.05	6	1	0.5	9	0.5	150	0.672159624	0.355068417
1536	0.05	6	1	0.5	11	0.5	150	0.672161173	0.355753846
1537	0.05	6	1	0.5	13	0.5	150	0.675457233	0.362398514
1538	0.05	6	1	0.5	15	0.5	150	0.67261361	0.356478058
1539	0.05	6	1	0.5	17	0.5	150	0.673562776	0.358704993
1540	0.05	6	1	0.5	19	0.5	150	0.674964895	0.362215262
1541	0.05	7	0	0.5	1	0.5	150	0.669433682	0.343177247
1542	0.05	7	0	0.5	3	0.5	150	0.669660052	0.344438643
1543	0.05	7	0	0.5	5	0.5	150	0.6716678	0.349039598
1544	0.05	7	0	0.5	7	0.5	150	0.669169867	0.344329616
1545	0.05	7	0	0.5	9	0.5	150	0.667878972	0.342334747
1546	0.05	7	0	0.5	11	0.5	150	0.670040777	0.347783885
1547	0.05	7	0	0.5	13	0.5	150	0.67200811	0.352735472
1548	0.05	7	0	0.5	15	0.5	150	0.672084771	0.352732945
1549	0.05	7	0	0.5	17	0.5	150	0.672047493	0.353820233
1550	0.05	7	0	0.5	19	0.5	150	0.674737406	0.359535947
1551	0.05	7	0.1	0.5	1	0.5	150	0.670536042	0.346053601
1552	0.05	7	0.1	0.5	3	0.5	150	0.668221387	0.340489469
1553	0.05	7	0.1	0.5	5	0.5	150	0.672654243	0.350218493
1554	0.05	7	0.1	0.5	7	0.5	150	0.67432134	0.354403723
1555	0.05	7	0.1	0.5	9	0.5	150	0.672126049	0.35120671
1556	0.05	7	0.1	0.5	11	0.5	150	0.667841955	0.342812135
1557	0.05	7	0.1	0.5	13	0.5	150	0.672427101	0.353356954
1558	0.05	7	0.1	0.5	15	0.5	150	0.673262155	0.355424278
1559	0.05	7	0.1	0.5	17	0.5	150	0.672462567	0.353814657
1560	0.05	7	0.1	0.5	19	0.5	150	0.675382896	0.360002097
1561	0.05	7	0.2	0.5	1	0.5	150	0.669356891	0.342813565
1562	0.05	7	0.2	0.5	3	0.5	150	0.668110248	0.341219563
1563	0.05	7	0.2	0.5	5	0.5	150	0.670873852	0.34742124
1564	0.05	7	0.2	0.5	7	0.5	150	0.669584123	0.345768589
1565	0.05	7	0.2	0.5	9	0.5	150	0.669015981	0.345116792
1566	0.05	7	0.2	0.5	11	0.5	150	0.672880959	0.353984574
1567	0.05	7	0.2	0.5	13	0.5	150	0.670645503	0.349995286
1568	0.05	7	0.2	0.5	15	0.5	150	0.672954734	0.354723721
1569	0.05	7	0.2	0.5	17	0.5	150	0.671666942	0.35284368
1570	0.05	7	0.2	0.5	19	0.5	150	0.672466142	0.35455599
1571	0.05	7	0.3	0.5	1	0.5	150	0.668903637	0.341046994
1572	0.05	7	0.3	0.5	3	0.5	150	0.668409921	0.341815309
1573	0.05	7	0.3	0.5	5	0.5	150	0.670685188	0.347105317
1574	0.05	7	0.3	0.5	7	0.5	150	0.669055067	0.344157041
1575	0.05	7	0.3	0.5	9	0.5	150	0.669963643	0.347118872
1576	0.05	7	0.3	0.5	11	0.5	150	0.670835716	0.349527797
1577	0.05	7	0.3	0.5	13	0.5	150	0.67174369	0.352484046
1578	0.05	7	0.3	0.5	15	0.5	150	0.671671029	0.3526372
1579	0.05	7	0.3	0.5	17	0.5	150	0.672312387	0.35441583
1580	0.05	7	0.3	0.5	19	0.5	150	0.672652479	0.355077442
1581	0.05	7	0.4	0.5	1	0.5	150	0.66818463	0.340572148
1582	0.05	7	0.4	0.5	3	0.5	150	0.668222852	0.341575378
1583	0.05	7	0.4	0.5	5	0.5	150	0.671442725	0.348107277
1584	0.05	7	0.4	0.5	7	0.5	150	0.671442379	0.349108146
1585	0.05	7	0.4	0.5	9	0.5	150	0.671478579	0.349694051
1586	0.05	7	0.4	0.5	11	0.5	150	0.67212394	0.351904877
1587	0.05	7	0.4	0.5	13	0.5	150	0.669623637	0.347870328
1588	0.05	7	0.4	0.5	15	0.5	150	0.672917845	0.355135908
1589	0.05	7	0.4	0.5	17	0.5	150	0.672920084	0.35538703
1590	0.05	7	0.4	0.5	19	0.5	150	0.673070869	0.355836496
1591	0.05	7	0.5	0.5	1	0.5	150	0.668791335	0.341671734
1592	0.05	7	0.5	0.5	3	0.5	150	0.669775711	0.344349248
1593	0.05	7	0.5	0.5	5	0.5	150	0.670306101	0.346035507
1594	0.05	7	0.5	0.5	7	0.5	150	0.672275884	0.35164814
1595	0.05	7	0.5	0.5	9	0.5	150	0.669738133	0.346810041
1596	0.05	7	0.5	0.5	11	0.5	150	0.671858487	0.351658678
1597	0.05	7	0.5	0.5	13	0.5	150	0.670569616	0.349719375
1598	0.05	7	0.5	0.5	15	0.5	150	0.672920043	0.355209003
1599	0.05	7	0.5	0.5	17	0.5	150	0.674700432	0.358842258
1600	0.05	7	0.5	0.5	19	0.5	150	0.671137757	0.352647572
1601	0.05	7	0.6	0.5	1	0.5	150	0.668864511	0.341961392
1602	0.05	7	0.6	0.5	3	0.5	150	0.669737617	0.34429365
1603	0.05	7	0.6	0.5	5	0.5	150	0.667692894	0.341000059
1604	0.05	7	0.6	0.5	7	0.5	150	0.670115804	0.347033505
1605	0.05	7	0.6	0.5	9	0.5	150	0.668184069	0.343263497
1606	0.05	7	0.6	0.5	11	0.5	150	0.670001091	0.347705017
1607	0.05	7	0.6	0.5	13	0.5	150	0.67042103	0.349363649
1608	0.05	7	0.6	0.5	15	0.5	150	0.669244676	0.347955857
1609	0.05	7	0.6	0.5	17	0.5	150	0.674473461	0.358807186
1610	0.05	7	0.6	0.5	19	0.5	150	0.672577109	0.355315541
1611	0.05	7	0.7	0.5	1	0.5	150	0.666329903	0.33689511
1612	0.05	7	0.7	0.5	3	0.5	150	0.670757764	0.346379924
1613	0.05	7	0.7	0.5	5	0.5	150	0.671176968	0.34868036
1614	0.05	7	0.7	0.5	7	0.5	150	0.669548483	0.3452854
1615	0.05	7	0.7	0.5	9	0.5	150	0.671138659	0.348994642
1616	0.05	7	0.7	0.5	11	0.5	150	0.672161302	0.352450838
1617	0.05	7	0.7	0.5	13	0.5	150	0.67003996	0.348407985
1618	0.05	7	0.7	0.5	15	0.5	150	0.67303303	0.355726682
1619	0.05	7	0.7	0.5	17	0.5	150	0.670873422	0.351390534
1620	0.05	7	0.7	0.5	19	0.5	150	0.672881818	0.355747257
1621	0.05	7	0.8	0.5	1	0.5	150	0.66787992	0.339812308
1622	0.05	7	0.8	0.5	3	0.5	150	0.671555584	0.348542065
1623	0.05	7	0.8	0.5	5	0.5	150	0.669889046	0.34534893
1624	0.05	7	0.8	0.5	7	0.5	150	0.671138576	0.348834391
1625	0.05	7	0.8	0.5	9	0.5	150	0.670230731	0.347621663
1626	0.05	7	0.8	0.5	11	0.5	150	0.669813892	0.347963687
1627	0.05	7	0.8	0.5	13	0.5	150	0.668941259	0.346464135
1628	0.05	7	0.8	0.5	15	0.5	150	0.673410484	0.355728539
1629	0.05	7	0.8	0.5	17	0.5	150	0.673412509	0.356120971
1630	0.05	7	0.8	0.5	19	0.5	150	0.672388232	0.354729787
1631	0.05	7	0.9	0.5	1	0.5	150	0.66837497	0.341226604
1632	0.05	7	0.9	0.5	3	0.5	150	0.670267577	0.345681576
1633	0.05	7	0.9	0.5	5	0.5	150	0.667274116	0.340032862
1634	0.05	7	0.9	0.5	7	0.5	150	0.669017705	0.344632743
1635	0.05	7	0.9	0.5	9	0.5	150	0.671363909	0.350136473
1636	0.05	7	0.9	0.5	11	0.5	150	0.672199396	0.352801818
1637	0.05	7	0.9	0.5	13	0.5	150	0.673486374	0.355799298
1638	0.05	7	0.9	0.5	15	0.5	150	0.673676887	0.356713312
1639	0.05	7	0.9	0.5	17	0.5	150	0.66992555	0.349694543
1640	0.05	7	0.9	0.5	19	0.5	150	0.67503936	0.36079739
1641	0.05	7	1	0.5	1	0.5	150	0.668486152	0.341332112
1642	0.05	7	1	0.5	3	0.5	150	0.669925977	0.344518436
1643	0.05	7	1	0.5	5	0.5	150	0.669014907	0.344220484
1644	0.05	7	1	0.5	7	0.5	150	0.670457744	0.347034913
1645	0.05	7	1	0.5	9	0.5	150	0.669586876	0.346459754
1646	0.05	7	1	0.5	11	0.5	150	0.66958477	0.346530679
1647	0.05	7	1	0.5	13	0.5	150	0.671402219	0.351167996
1648	0.05	7	1	0.5	15	0.5	150	0.671971177	0.352830054
1649	0.05	7	1	0.5	17	0.5	150	0.673257765	0.356069606
1650	0.05	7	1	0.5	19	0.5	150	0.673675251	0.35797419

#	eta	max_depth	gamma	colsample_bytree	min_child_weight	subsample	nrounds	Accuracy	Kappa
1651	0.05	8	0	0.5	1	0.5	150	0.666821466	0.334089239
1652	0.05	8	0	0.5	3	0.5	150	0.666935101	0.335759177
1653	0.05	8	0	0.5	5	0.5	150	0.66810956	0.339002421
1654	0.05	8	0	0.5	7	0.5	150	0.666820045	0.336943938
1655	0.05	8	0	0.5	9	0.5	150	0.665342813	0.33546326
1656	0.05	8	0	0.5	11	0.5	150	0.668978662	0.343577021
1657	0.05	8	0	0.5	13	0.5	150	0.671894515	0.350238634
1658	0.05	8	0	0.5	15	0.5	150	0.668865115	0.345521745
1659	0.05	8	0	0.5	17	0.5	150	0.670456455	0.349555904
1660	0.05	8	0	0.5	19	0.5	150	0.672429511	0.353582692
1661	0.05	8	0.1	0.5	1	0.5	150	0.662920162	0.325956732
1662	0.05	8	0.1	0.5	3	0.5	150	0.666479911	0.334350071
1663	0.05	8	0.1	0.5	5	0.5	150	0.666291204	0.335291831
1664	0.05	8	0.1	0.5	7	0.5	150	0.667654066	0.339135879
1665	0.05	8	0.1	0.5	9	0.5	150	0.665946249	0.336764194
1666	0.05	8	0.1	0.5	11	0.5	150	0.67004267	0.345728325
1667	0.05	8	0.1	0.5	13	0.5	150	0.669169178	0.34529545
1668	0.05	8	0.1	0.5	15	0.5	150	0.671783806	0.350711538
1669	0.05	8	0.1	0.5	17	0.5	150	0.672806792	0.353330107
1670	0.05	8	0.1	0.5	19	0.5	150	0.672956587	0.355053013
1671	0.05	8	0.2	0.5	1	0.5	150	0.666819828	0.334611069
1672	0.05	8	0.2	0.5	3	0.5	150	0.668411601	0.338599317
1673	0.05	8	0.2	0.5	5	0.5	150	0.666592643	0.336023354
1674	0.05	8	0.2	0.5	7	0.5	150	0.668108699	0.339694691
1675	0.05	8	0.2	0.5	9	0.5	150	0.66803195	0.340643607
1676	0.05	8	0.2	0.5	11	0.5	150	0.666669089	0.338880579
1677	0.05	8	0.2	0.5	13	0.5	150	0.669889606	0.346080123
1678	0.05	8	0.2	0.5	15	0.5	150	0.669850609	0.347553576
1679	0.05	8	0.2	0.5	17	0.5	150	0.671973458	0.351548089
1680	0.05	8	0.2	0.5	19	0.5	150	0.672047408	0.352522218
1681	0.05	8	0.3	0.5	1	0.5	150	0.66393936	0.328107689
1682	0.05	8	0.3	0.5	3	0.5	150	0.665570129	0.332711975
1683	0.05	8	0.3	0.5	5	0.5	150	0.670116662	0.342478692
1684	0.05	8	0.3	0.5	7	0.5	150	0.666176752	0.335708977
1685	0.05	8	0.3	0.5	9	0.5	150	0.668447672	0.341201771
1686	0.05	8	0.3	0.5	11	0.5	150	0.670380224	0.346603839
1687	0.05	8	0.3	0.5	13	0.5	150	0.669967215	0.346438953
1688	0.05	8	0.3	0.5	15	0.5	150	0.669813978	0.346386744
1689	0.05	8	0.3	0.5	17	0.5	150	0.673601084	0.355601894
1690	0.05	8	0.3	0.5	19	0.5	150	0.669623509	0.348405564
1691	0.05	8	0.4	0.5	1	0.5	150	0.664812856	0.330552317
1692	0.05	8	0.4	0.5	3	0.5	150	0.667993943	0.33740043
1693	0.05	8	0.4	0.5	5	0.5	150	0.667577836	0.338029782
1694	0.05	8	0.4	0.5	7	0.5	150	0.66875251	0.341345503
1695	0.05	8	0.4	0.5	9	0.5	150	0.668826587	0.34170702
1696	0.05	8	0.4	0.5	11	0.5	150	0.670611069	0.346937754
1697	0.05	8	0.4	0.5	13	0.5	150	0.669623808	0.345572717
1698	0.05	8	0.4	0.5	15	0.5	150	0.670040305	0.347482083
1699	0.05	8	0.4	0.5	17	0.5	150	0.673374373	0.354717933
1700	0.05	8	0.4	0.5	19	0.5	150	0.673941434	0.356262741
1701	0.05	8	0.5	0.5	1	0.5	150	0.666667539	0.334238139
1702	0.05	8	0.5	0.5	3	0.5	150	0.664660909	0.331106053
1703	0.05	8	0.5	0.5	5	0.5	150	0.665760298	0.333358943
1704	0.05	8	0.5	0.5	7	0.5	150	0.666593374	0.336724358
1705	0.05	8	0.5	0.5	9	0.5	150	0.665685229	0.335581005
1706	0.05	8	0.5	0.5	11	0.5	150	0.670569273	0.346891139
1707	0.05	8	0.5	0.5	13	0.5	150	0.671063505	0.348455058
1708	0.05	8	0.5	0.5	15	0.5	150	0.670985811	0.349166775
1709	0.05	8	0.5	0.5	17	0.5	150	0.670343464	0.348752558
1710	0.05	8	0.5	0.5	19	0.5	150	0.673373899	0.355087492
1711	0.05	8	0.6	0.5	1	0.5	150	0.665002893	0.330429402
1712	0.05	8	0.6	0.5	3	0.5	150	0.670039872	0.34242686
1713	0.05	8	0.6	0.5	5	0.5	150	0.666252723	0.335117249
1714	0.05	8	0.6	0.5	7	0.5	150	0.668146363	0.339745875
1715	0.05	8	0.6	0.5	9	0.5	150	0.669813461	0.344049863
1716	0.05	8	0.6	0.5	11	0.5	150	0.668449263	0.342280417
1717	0.05	8	0.6	0.5	13	0.5	150	0.668827363	0.344652277
1718	0.05	8	0.6	0.5	15	0.5	150	0.67064658	0.348592107
1719	0.05	8	0.6	0.5	17	0.5	150	0.67079874	0.34942239
1720	0.05	8	0.6	0.5	19	0.5	150	0.671518741	0.35217182
1721	0.05	8	0.7	0.5	1	0.5	150	0.667803816	0.336923069
1722	0.05	8	0.7	0.5	3	0.5	150	0.665872988	0.332570244
1723	0.05	8	0.7	0.5	5	0.5	150	0.666366318	0.334088582
1724	0.05	8	0.7	0.5	7	0.5	150	0.666592427	0.33783143
1725	0.05	8	0.7	0.5	9	0.5	150	0.668220442	0.341224325
1726	0.05	8	0.7	0.5	11	0.5	150	0.667539441	0.340519698
1727	0.05	8	0.7	0.5	13	0.5	150	0.671027693	0.349213648
1728	0.05	8	0.7	0.5	15	0.5	150	0.670569488	0.348348866
1729	0.05	8	0.7	0.5	17	0.5	150	0.670683814	0.348899357
1730	0.05	8	0.7	0.5	19	0.5	150	0.672692466	0.353739074
1731	0.05	8	0.8	0.5	1	0.5	150	0.664776223	0.330464707
1732	0.05	8	0.8	0.5	3	0.5	150	0.66712187	0.33556659
1733	0.05	8	0.8	0.5	5	0.5	150	0.668372688	0.339155406
1734	0.05	8	0.8	0.5	7	0.5	150	0.666477242	0.33653957
1735	0.05	8	0.8	0.5	9	0.5	150	0.668638226	0.342335325
1736	0.05	8	0.8	0.5	11	0.5	150	0.670871271	0.347393842
1737	0.05	8	0.8	0.5	13	0.5	150	0.67265532	0.351537508
1738	0.05	8	0.8	0.5	15	0.5	150	0.671140125	0.349971677
1739	0.05	8	0.8	0.5	17	0.5	150	0.671745625	0.352177137
1740	0.05	8	0.8	0.5	19	0.5	150	0.671176884	0.351239141
1741	0.05	8	0.9	0.5	1	0.5	150	0.663564576	0.327475755
1742	0.05	8	0.9	0.5	3	0.5	150	0.665607404	0.333037109
1743	0.05	8	0.9	0.5	5	0.5	150	0.665266842	0.332757483
1744	0.05	8	0.9	0.5	7	0.5	150	0.666136978	0.336209224
1745	0.05	8	0.9	0.5	9	0.5	150	0.670193413	0.345026356
1746	0.05	8	0.9	0.5	11	0.5	150	0.66977515	0.345509246
1747	0.05	8	0.9	0.5	13	0.5	150	0.669927657	0.346648522
1748	0.05	8	0.9	0.5	15	0.5	150	0.671592517	0.350775441
1749	0.05	8	0.9	0.5	17	0.5	150	0.670494764	0.349655872
1750	0.05	8	0.9	0.5	19	0.5	150	0.669470572	0.347905106
1751	0.05	8	1	0.5	1	0.5	150	0.66659234	0.333976642
1752	0.05	8	1	0.5	3	0.5	150	0.667539139	0.33738617
1753	0.05	8	1	0.5	5	0.5	150	0.667426019	0.337698542
1754	0.05	8	1	0.5	7	0.5	150	0.669093764	0.342480513
1755	0.05	8	1	0.5	9	0.5	150	0.668938976	0.342661913
1756	0.05	8	1	0.5	11	0.5	150	0.669619934	0.344605066
1757	0.05	8	1	0.5	13	0.5	150	0.670872434	0.349025528
1758	0.05	8	1	0.5	15	0.5	150	0.670306317	0.347877559
1759	0.05	8	1	0.5	17	0.5	150	0.671138832	0.350864736
1760	0.05	8	1	0.5	19	0.5	150	0.672918319	0.355056079
1761	0.05	9	0	0.5	1	0.5	150	0.665721386	0.329010644
1762	0.05	9	0	0.5	3	0.5	150	0.663600301	0.325004202
1763	0.05	9	0	0.5	5	0.5	150	0.665343115	0.330571786
1764	0.05	9	0	0.5	7	0.5	150	0.668525925	0.338939364
1765	0.05	9	0	0.5	9	0.5	150	0.666441385	0.334800585
1766	0.05	9	0	0.5	11	0.5	150	0.666516412	0.337672984
1767	0.05	9	0	0.5	13	0.5	150	0.668182089	0.341847899
1768	0.05	9	0	0.5	15	0.5	150	0.671517449	0.34956495
1769	0.05	9	0	0.5	17	0.5	150	0.671063593	0.348161653
1770	0.05	9	0	0.5	19	0.5	150	0.670571468	0.348858905
1771	0.05	9	0.1	0.5	1	0.5	150	0.665267701	0.327530317
1772	0.05	9	0.1	0.5	3	0.5	150	0.665758836	0.32986446
1773	0.05	9	0.1	0.5	5	0.5	150	0.66507861	0.32954713
1774	0.05	9	0.1	0.5	7	0.5	150	0.665493941	0.33237118
1775	0.05	9	0.1	0.5	9	0.5	150	0.668297621	0.339486173
1776	0.05	9	0.1	0.5	11	0.5	150	0.666821639	0.337829945
1777	0.05	9	0.1	0.5	13	0.5	150	0.668335671	0.341993197
1778	0.05	9	0.1	0.5	15	0.5	150	0.668109388	0.342201936
1779	0.05	9	0.1	0.5	17	0.5	150	0.669358227	0.345837571
1780	0.05	9	0.1	0.5	19	0.5	150	0.669887671	0.347112663
1781	0.05	9	0.2	0.5	1	0.5	150	0.663827446	0.325309306
1782	0.05	9	0.2	0.5	3	0.5	150	0.665949909	0.330931588
1783	0.05	9	0.2	0.5	5	0.5	150	0.664852671	0.329093792
1784	0.05	9	0.2	0.5	7	0.5	150	0.667578913	0.337173884
1785	0.05	9	0.2	0.5	9	0.5	150	0.668183381	0.33936513
1786	0.05	9	0.2	0.5	11	0.5	150	0.665872342	0.336548934
1787	0.05	9	0.2	0.5	13	0.5	150	0.667691301	0.339981808
1788	0.05	9	0.2	0.5	15	0.5	150	0.669811437	0.345305539
1789	0.05	9	0.2	0.5	17	0.5	150	0.670608702	0.347807674
1790	0.05	9	0.2	0.5	19	0.5	150	0.673261123	0.353731722
1791	0.05	9	0.3	0.5	1	0.5	150	0.663182817	0.323132191
1792	0.05	9	0.3	0.5	3	0.5	150	0.662194696	0.322346854
1793	0.05	9	0.3	0.5	5	0.5	150	0.666138183	0.332041678
1794	0.05	9	0.3	0.5	7	0.5	150	0.665457828	0.332794521
1795	0.05	9	0.3	0.5	9	0.5	150	0.665762365	0.334885374
1796	0.05	9	0.3	0.5	11	0.5	150	0.669014734	0.342273033
1797	0.05	9	0.3	0.5	13	0.5	150	0.669471993	0.344114991
1798	0.05	9	0.3	0.5	15	0.5	150	0.668675074	0.343585024
1799	0.05	9	0.3	0.5	17	0.5	150	0.669735335	0.346213854
1800	0.05	9	0.3	0.5	19	0.5	150	0.673790823	0.355329541

#	eta	max_depth	gamma	colsample_bytree	min_child_weight	subsample	nrounds	Accuracy	Kappa
1801	0.05	9	0.4	0.5	1	0.5	150	0.662691339	0.32315068
1802	0.05	9	0.4	0.5	3	0.5	150	0.665151696	0.328399322
1803	0.05	9	0.4	0.5	5	0.5	150	0.666518304	0.333194034
1804	0.05	9	0.4	0.5	7	0.5	150	0.666972591	0.335137325
1805	0.05	9	0.4	0.5	9	0.5	150	0.665000569	0.332433904
1806	0.05	9	0.4	0.5	11	0.5	150	0.667652387	0.338893744
1807	0.05	9	0.4	0.5	13	0.5	150	0.669473154	0.343622205
1808	0.05	9	0.4	0.5	15	0.5	150	0.6676149	0.341778922
1809	0.05	9	0.4	0.5	17	0.5	150	0.668790992	0.344361514
1810	0.05	9	0.4	0.5	19	0.5	150	0.671024852	0.349645692
1811	0.05	9	0.5	0.5	1	0.5	150	0.662576069	0.322310124
1812	0.05	9	0.5	0.5	3	0.5	150	0.66318411	0.324829277
1813	0.05	9	0.5	0.5	5	0.5	150	0.6648893	0.329862439
1814	0.05	9	0.5	0.5	7	0.5	150	0.666708	0.334991966
1815	0.05	9	0.5	0.5	9	0.5	150	0.666329685	0.335363138
1816	0.05	9	0.5	0.5	11	0.5	150	0.66602515	0.336304501
1817	0.05	9	0.5	0.5	13	0.5	150	0.669814495	0.344936886
1818	0.05	9	0.5	0.5	15	0.5	150	0.669963256	0.346526719
1819	0.05	9	0.5	0.5	17	0.5	150	0.670797622	0.348528877
1820	0.05	9	0.5	0.5	19	0.5	150	0.669776014	0.347257795
1821	0.05	9	0.6	0.5	1	0.5	150	0.663370705	0.323112052
1822	0.05	9	0.6	0.5	3	0.5	150	0.666405012	0.331233594
1823	0.05	9	0.6	0.5	5	0.5	150	0.664660521	0.329319307
1824	0.05	9	0.6	0.5	7	0.5	150	0.666100003	0.333748379
1825	0.05	9	0.6	0.5	9	0.5	150	0.669395158	0.341690072
1826	0.05	9	0.6	0.5	11	0.5	150	0.667086099	0.338956068
1827	0.05	9	0.6	0.5	13	0.5	150	0.671821513	0.349358302
1828	0.05	9	0.6	0.5	15	0.5	150	0.670227373	0.346981193
1829	0.05	9	0.6	0.5	17	0.5	150	0.670457488	0.348670882
1830	0.05	9	0.6	0.5	19	0.5	150	0.671063032	0.350127057
1831	0.05	9	0.7	0.5	1	0.5	150	0.659132411	0.315675541
1832	0.05	9	0.7	0.5	3	0.5	150	0.666175114	0.330738411
1833	0.05	9	0.7	0.5	5	0.5	150	0.666518562	0.333528507
1834	0.05	9	0.7	0.5	7	0.5	150	0.666289225	0.333846298
1835	0.05	9	0.7	0.5	9	0.5	150	0.665192891	0.332307832
1836	0.05	9	0.7	0.5	11	0.5	150	0.669281822	0.342668382
1837	0.05	9	0.7	0.5	13	0.5	150	0.668827923	0.343103452
1838	0.05	9	0.7	0.5	15	0.5	150	0.668258063	0.343212205
1839	0.05	9	0.7	0.5	17	0.5	150	0.671289357	0.349962186
1840	0.05	9	0.7	0.5	19	0.5	150	0.671631732	0.351999319
1841	0.05	9	0.8	0.5	1	0.5	150	0.66488775	0.327638759
1842	0.05	9	0.8	0.5	3	0.5	150	0.664812123	0.328599445
1843	0.05	9	0.8	0.5	5	0.5	150	0.66689619	0.335140782
1844	0.05	9	0.8	0.5	7	0.5	150	0.668979697	0.339856288
1845	0.05	9	0.8	0.5	9	0.5	150	0.666251088	0.335995698
1846	0.05	9	0.8	0.5	11	0.5	150	0.669773689	0.344188323
1847	0.05	9	0.8	0.5	13	0.5	150	0.669054165	0.343999308
1848	0.05	9	0.8	0.5	15	0.5	150	0.669017145	0.344506352
1849	0.05	9	0.8	0.5	17	0.5	150	0.670379793	0.348668248
1850	0.05	9	0.8	0.5	19	0.5	150	0.672123725	0.352074465
1851	0.05	9	0.9	0.5	1	0.5	150	0.665836874	0.32900883
1852	0.05	9	0.9	0.5	3	0.5	150	0.664318193	0.327848484
1853	0.05	9	0.9	0.5	5	0.5	150	0.666555452	0.334366168
1854	0.05	9	0.9	0.5	7	0.5	150	0.667048135	0.335972854
1855	0.05	9	0.9	0.5	9	0.5	150	0.666063157	0.335151183
1856	0.05	9	0.9	0.5	11	0.5	150	0.667766154	0.340550111
1857	0.05	9	0.9	0.5	13	0.5	150	0.669092817	0.344221658
1858	0.05	9	0.9	0.5	15	0.5	150	0.668600907	0.344133381
1859	0.05	9	0.9	0.5	17	0.5	150	0.670193414	0.347557369
1860	0.05	9	0.9	0.5	19	0.5	150	0.672654846	0.353406598
1861	0.05	9	1	0.5	1	0.5	150	0.662498544	0.322806929
1862	0.05	9	1	0.5	3	0.5	150	0.668525321	0.336046826
1863	0.05	9	1	0.5	5	0.5	150	0.665190564	0.331477702
1864	0.05	9	1	0.5	7	0.5	150	0.665758878	0.333994645
1865	0.05	9	1	0.5	9	0.5	150	0.665910566	0.33470781
1866	0.05	9	1	0.5	11	0.5	150	0.667085024	0.338825698
1867	0.05	9	1	0.5	13	0.5	150	0.667956538	0.34246484
1868	0.05	9	1	0.5	15	0.5	150	0.669281954	0.344863881
1869	0.05	9	1	0.5	17	0.5	150	0.67121614	0.34958186
1870	0.05	9	1	0.5	19	0.5	150	0.671365718	0.350975493
1871	0.05	10	0	0.5	1	0.5	150	0.660456102	0.316121669
1872	0.05	10	0	0.5	3	0.5	150	0.662654623	0.321728413
1873	0.05	10	0	0.5	5	0.5	150	0.663071205	0.324206233
1874	0.05	10	0	0.5	7	0.5	150	0.667425031	0.334712825
1875	0.05	10	0	0.5	9	0.5	150	0.668600478	0.338793529
1876	0.05	10	0	0.5	11	0.5	150	0.667273515	0.337930545
1877	0.05	10	0	0.5	13	0.5	150	0.668448834	0.341417149
1878	0.05	10	0	0.5	15	0.5	150	0.670230516	0.345625828
1879	0.05	10	0	0.5	17	0.5	150	0.671934243	0.350564808
1880	0.05	10	0	0.5	19	0.5	150	0.670305629	0.348220157
1881	0.05	10	0.1	0.5	1	0.5	150	0.659774328	0.314229347
1882	0.05	10	0.1	0.5	3	0.5	150	0.66375186	0.324026383
1883	0.05	10	0.1	0.5	5	0.5	150	0.662274799	0.322711034
1884	0.05	10	0.1	0.5	7	0.5	150	0.664960366	0.330066388
1885	0.05	10	0.1	0.5	9	0.5	150	0.66291702	0.328301557
1886	0.05	10	0.1	0.5	11	0.5	150	0.66715949	0.336982385
1887	0.05	10	0.1	0.5	13	0.5	150	0.668221646	0.341008251
1888	0.05	10	0.1	0.5	15	0.5	150	0.667691686	0.340491745
1889	0.05	10	0.1	0.5	17	0.5	150	0.671593121	0.349841209
1890	0.05	10	0.1	0.5	19	0.5	150	0.670380439	0.3479391
1891	0.05	10	0.2	0.5	1	0.5	150	0.661971298	0.319000023
1892	0.05	10	0.2	0.5	3	0.5	150	0.664054376	0.324609347
1893	0.05	10	0.2	0.5	5	0.5	150	0.663448573	0.324468351
1894	0.05	10	0.2	0.5	7	0.5	150	0.66420615	0.328539589
1895	0.05	10	0.2	0.5	9	0.5	150	0.666137495	0.33399443
1896	0.05	10	0.2	0.5	11	0.5	150	0.664965447	0.333985759
1897	0.05	10	0.2	0.5	13	0.5	150	0.669852504	0.343941856
1898	0.05	10	0.2	0.5	15	0.5	150	0.670115975	0.346215554
1899	0.05	10	0.2	0.5	17	0.5	150	0.669132117	0.344262907
1900	0.05	10	0.2	0.5	19	0.5	150	0.671896365	0.350899534
1901	0.05	10	0.3	0.5	1	0.5	150	0.659850297	0.314064704
1902	0.05	10	0.3	0.5	3	0.5	150	0.665039094	0.326855582
1903	0.05	10	0.3	0.5	5	0.5	150	0.665835237	0.33012875
1904	0.05	10	0.3	0.5	7	0.5	150	0.665303902	0.33039992
1905	0.05	10	0.3	0.5	9	0.5	150	0.666932476	0.336046121
1906	0.05	10	0.3	0.5	11	0.5	150	0.667350089	0.337478148
1907	0.05	10	0.3	0.5	13	0.5	150	0.667313157	0.339194145
1908	0.05	10	0.3	0.5	15	0.5	150	0.667805842	0.341227638
1909	0.05	10	0.3	0.5	17	0.5	150	0.670494505	0.347276129
1910	0.05	10	0.3	0.5	19	0.5	150	0.671594756	0.35023374
1911	0.05	10	0.4	0.5	1	0.5	150	0.661100903	0.316881774
1912	0.05	10	0.4	0.5	3	0.5	150	0.664018175	0.324527366
1913	0.05	10	0.4	0.5	5	0.5	150	0.663259607	0.324921365
1914	0.05	10	0.4	0.5	7	0.5	150	0.664206753	0.328545456
1915	0.05	10	0.4	0.5	9	0.5	150	0.66753858	0.337022374
1916	0.05	10	0.4	0.5	11	0.5	150	0.666063673	0.334725133
1917	0.05	10	0.4	0.5	13	0.5	150	0.666743338	0.337742547
1918	0.05	10	0.4	0.5	15	0.5	150	0.66844922	0.342140632
1919	0.05	10	0.4	0.5	17	0.5	150	0.671897658	0.349991801
1920	0.05	10	0.4	0.5	19	0.5	150	0.671518611	0.350547773
1921	0.05	10	0.5	0.5	1	0.5	150	0.660722546	0.316042744
1922	0.05	10	0.5	0.5	3	0.5	150	0.662842811	0.322046503
1923	0.05	10	0.5	0.5	5	0.5	150	0.662917234	0.323880498
1924	0.05	10	0.5	0.5	7	0.5	150	0.664775707	0.329729978
1925	0.05	10	0.5	0.5	9	0.5	150	0.665533156	0.332546106
1926	0.05	10	0.5	0.5	11	0.5	150	0.667615887	0.33851123
1927	0.05	10	0.5	0.5	13	0.5	150	0.666402948	0.337179205
1928	0.05	10	0.5	0.5	15	0.5	150	0.669358141	0.344228177
1929	0.05	10	0.5	0.5	17	0.5	150	0.670568842	0.347842117
1930	0.05	10	0.5	0.5	19	0.5	150	0.670266802	0.347466241
1931	0.05	10	0.6	0.5	1	0.5	150	0.662955028	0.320078072
1932	0.05	10	0.6	0.5	3	0.5	150	0.665305536	0.326120564
1933	0.05	10	0.6	0.5	5	0.5	150	0.667122689	0.332753689
1934	0.05	10	0.6	0.5	7	0.5	150	0.666592169	0.333282383
1935	0.05	10	0.6	0.5	9	0.5	150	0.664888826	0.331036142
1936	0.05	10	0.6	0.5	11	0.5	150	0.665684153	0.334161022
1937	0.05	10	0.6	0.5	13	0.5	150	0.669851512	0.343654814
1938	0.05	10	0.6	0.5	15	0.5	150	0.665758577	0.337005935
1939	0.05	10	0.6	0.5	17	0.5	150	0.669737919	0.345944609
1940	0.05	10	0.6	0.5	19	0.5	150	0.670532643	0.348544503
1941	0.05	10	0.7	0.5	1	0.5	150	0.66242623	0.319809029
1942	0.05	10	0.7	0.5	3	0.5	150	0.6642445	0.325573088
1943	0.05	10	0.7	0.5	5	0.5	150	0.661971729	0.322394156
1944	0.05	10	0.7	0.5	7	0.5	150	0.667652175	0.33617129
1945	0.05	10	0.7	0.5	9	0.5	150	0.664167065	0.329436896
1946	0.05	10	0.7	0.5	11	0.5	150	0.667577449	0.338590011
1947	0.05	10	0.7	0.5	13	0.5	150	0.666857881	0.338353001
1948	0.05	10	0.7	0.5	15	0.5	150	0.669171889	0.343883197
1949	0.05	10	0.7	0.5	17	0.5	150	0.670379706	0.347893496
1950	0.05	10	0.7	0.5	19	0.5	150	0.672616796	0.352695367

#	eta	max_depth	gamma	colsample_bytree	min_child_weight	subsample	nrounds	Accuracy	Kappa
1951	0.05	10	0.8	0.5	1	0.5	150	0.6654942	0.326182073
1952	0.05	10	0.8	0.5	3	0.5	150	0.663638696	0.323575174
1953	0.05	10	0.8	0.5	5	0.5	150	0.666745838	0.332313691
1954	0.05	10	0.8	0.5	7	0.5	150	0.660456016	0.320900489
1955	0.05	10	0.8	0.5	9	0.5	150	0.667426879	0.336742927
1956	0.05	10	0.8	0.5	11	0.5	150	0.666857707	0.336990241
1957	0.05	10	0.8	0.5	13	0.5	150	0.668638098	0.341531361
1958	0.05	10	0.8	0.5	15	0.5	150	0.668865888	0.343881632
1959	0.05	10	0.8	0.5	17	0.5	150	0.672425765	0.351866802
1960	0.05	10	0.8	0.5	19	0.5	150	0.672614986	0.352374613
1961	0.05	10	0.9	0.5	1	0.5	150	0.662728529	0.321158502
1962	0.05	10	0.9	0.5	3	0.5	150	0.662462689	0.321736915
1963	0.05	10	0.9	0.5	5	0.5	150	0.663181353	0.324872941
1964	0.05	10	0.9	0.5	7	0.5	150	0.666628971	0.334016146
1965	0.05	10	0.9	0.5	9	0.5	150	0.665532639	0.332859463
1966	0.05	10	0.9	0.5	11	0.5	150	0.667349918	0.338042118
1967	0.05	10	0.9	0.5	13	0.5	150	0.66871446	0.342570934
1968	0.05	10	0.9	0.5	15	0.5	150	0.67170852	0.349578928
1969	0.05	10	0.9	0.5	17	0.5	150	0.669014003	0.344782143
1970	0.05	10	0.9	0.5	19	0.5	150	0.669813332	0.347422708
1971	0.05	10	1	0.5	1	0.5	150	0.663640764	0.323415268
1972	0.05	10	1	0.5	3	0.5	150	0.664926448	0.327538791
1973	0.05	10	1	0.5	5	0.5	150	0.662579381	0.323846013
1974	0.05	10	1	0.5	7	0.5	150	0.663336656	0.327310689
1975	0.05	10	1	0.5	9	0.5	150	0.665191903	0.332023555
1976	0.05	10	1	0.5	11	0.5	150	0.667161987	0.3380154
1977	0.05	10	1	0.5	13	0.5	150	0.667615242	0.340171334
1978	0.05	10	1	0.5	15	0.5	150	0.667616749	0.341822821
1979	0.05	10	1	0.5	17	0.5	150	0.669319144	0.345768375
1980	0.05	10	1	0.5	19	0.5	150	0.671025842	0.350095977
1981	0.05	5	0	0.5	1	0.5	200	0.671820996	0.352619345
1982	0.05	5	0	0.5	3	0.5	200	0.673676929	0.35726288
1983	0.05	5	0	0.5	5	0.5	200	0.675493259	0.361166139
1984	0.05	5	0	0.5	7	0.5	200	0.672237921	0.354331863
1985	0.05	5	0	0.5	9	0.5	200	0.67367568	0.357715384
1986	0.05	5	0	0.5	11	0.5	200	0.673751524	0.358613962
1987	0.05	5	0	0.5	13	0.5	200	0.670950901	0.353413316
1988	0.05	5	0	0.5	15	0.5	200	0.67378923	0.358508428
1989	0.05	5	0	0.5	17	0.5	200	0.674246402	0.359479019
1990	0.05	5	0	0.5	19	0.5	200	0.674888878	0.361005188
1991	0.05	5	0.1	0.5	1	0.5	200	0.673296375	0.356541242
1992	0.05	5	0.1	0.5	3	0.5	200	0.674852377	0.359088712
1993	0.05	5	0.1	0.5	5	0.5	200	0.672842905	0.355627316
1994	0.05	5	0.1	0.5	7	0.5	200	0.670455291	0.351173388
1995	0.05	5	0.1	0.5	9	0.5	200	0.672916296	0.356291876
1996	0.05	5	0.1	0.5	11	0.5	200	0.670607496	0.352140194
1997	0.05	5	0.1	0.5	13	0.5	200	0.674321429	0.359812187
1998	0.05	5	0.1	0.5	15	0.5	200	0.67155494	0.354651083
1999	0.05	5	0.1	0.5	17	0.5	200	0.674052445	0.359540547
2000	0.05	5	0.1	0.5	19	0.5	200	0.67553282	0.362185671
2001	0.05	5	0.2	0.5	1	0.5	200	0.670381729	0.350633738
2002	0.05	5	0.2	0.5	3	0.5	200	0.673904158	0.357719719
2003	0.05	5	0.2	0.5	5	0.5	200	0.672234306	0.354779638
2004	0.05	5	0.2	0.5	7	0.5	200	0.672993043	0.356070161
2005	0.05	5	0.2	0.5	9	0.5	200	0.67204969	0.355121342
2006	0.05	5	0.2	0.5	11	0.5	200	0.674245069	0.359309169
2007	0.05	5	0.2	0.5	13	0.5	200	0.673902738	0.358124567
2008	0.05	5	0.2	0.5	15	0.5	200	0.673334985	0.357797723
2009	0.05	5	0.2	0.5	17	0.5	200	0.672275155	0.354976581
2010	0.05	5	0.2	0.5	19	0.5	200	0.67492637	0.361430697
2011	0.05	5	0.3	0.5	1	0.5	200	0.673676711	0.357062057
2012	0.05	5	0.3	0.5	3	0.5	200	0.672916425	0.355265263
2013	0.05	5	0.3	0.5	5	0.5	200	0.674318586	0.358169801
2014	0.05	5	0.3	0.5	7	0.5	200	0.672541208	0.355686441
2015	0.05	5	0.3	0.5	9	0.5	200	0.672654114	0.355599416
2016	0.05	5	0.3	0.5	11	0.5	200	0.671933772	0.355121964
2017	0.05	5	0.3	0.5	13	0.5	200	0.672350138	0.356232687
2018	0.05	5	0.3	0.5	15	0.5	200	0.673068327	0.35765419
2019	0.05	5	0.3	0.5	17	0.5	200	0.673145764	0.357897977
2020	0.05	5	0.3	0.5	19	0.5	200	0.675040309	0.361423986
2021	0.05	5	0.4	0.5	1	0.5	200	0.67382741	0.356919627
2022	0.05	5	0.4	0.5	3	0.5	200	0.673563334	0.356334654
2023	0.05	5	0.4	0.5	5	0.5	200	0.67447122	0.359046847
2024	0.05	5	0.4	0.5	7	0.5	200	0.674472298	0.359299763
2025	0.05	5	0.4	0.5	9	0.5	200	0.671630656	0.354060783
2026	0.05	5	0.4	0.5	11	0.5	200	0.67397742	0.359177135
2027	0.05	5	0.4	0.5	13	0.5	200	0.674508713	0.360241106
2028	0.05	5	0.4	0.5	15	0.5	200	0.672918835	0.35696326
2029	0.05	5	0.4	0.5	17	0.5	200	0.671213128	0.353493033
2030	0.05	5	0.4	0.5	19	0.5	200	0.675040437	0.361192311
2031	0.05	5	0.5	0.5	1	0.5	200	0.673145548	0.355848998
2032	0.05	5	0.5	0.5	3	0.5	200	0.673865246	0.357848226
2033	0.05	5	0.5	0.5	5	0.5	200	0.673030491	0.356224482
2034	0.05	5	0.5	0.5	7	0.5	200	0.675003979	0.360252749
2035	0.05	5	0.5	0.5	9	0.5	200	0.672275455	0.354219088
2036	0.05	5	0.5	0.5	11	0.5	200	0.67291776	0.356763214
2037	0.05	5	0.5	0.5	13	0.5	200	0.672807221	0.356712349
2038	0.05	5	0.5	0.5	15	0.5	200	0.670835199	0.352522359
2039	0.05	5	0.5	0.5	17	0.5	200	0.675001783	0.361373242
2040	0.05	5	0.5	0.5	19	0.5	200	0.673902823	0.358930949
2041	0.05	5	0.6	0.5	1	0.5	200	0.673371701	0.356658846
2042	0.05	5	0.6	0.5	3	0.5	200	0.670719626	0.350799725
2043	0.05	5	0.6	0.5	5	0.5	200	0.670760475	0.350760479
2044	0.05	5	0.6	0.5	7	0.5	200	0.672767105	0.35587982
2045	0.05	5	0.6	0.5	9	0.5	200	0.673107325	0.356024827
2046	0.05	5	0.6	0.5	11	0.5	200	0.672576376	0.355995209
2047	0.05	5	0.6	0.5	13	0.5	200	0.672805028	0.357134707
2048	0.05	5	0.6	0.5	15	0.5	200	0.674432781	0.360365946
2049	0.05	5	0.6	0.5	17	0.5	200	0.673031182	0.35761684
2050	0.05	5	0.6	0.5	19	0.5	200	0.674206156	0.359921827
2051	0.05	5	0.7	0.5	1	0.5	200	0.673864085	0.357164252
2052	0.05	5	0.7	0.5	3	0.5	200	0.672426455	0.354437635
2053	0.05	5	0.7	0.5	5	0.5	200	0.672690873	0.355880863
2054	0.05	5	0.7	0.5	7	0.5	200	0.672918404	0.356426994
2055	0.05	5	0.7	0.5	9	0.5	200	0.67386331	0.358365196
2056	0.05	5	0.7	0.5	11	0.5	200	0.673335803	0.357054641
2057	0.05	5	0.7	0.5	13	0.5	200	0.674094673	0.359531118
2058	0.05	5	0.7	0.5	15	0.5	200	0.67371541	0.359096163
2059	0.05	5	0.7	0.5	17	0.5	200	0.674244206	0.35999038
2060	0.05	5	0.7	0.5	19	0.5	200	0.673525586	0.358511456
2061	0.05	5	0.8	0.5	1	0.5	200	0.671933383	0.353891945
2062	0.05	5	0.8	0.5	3	0.5	200	0.672085801	0.354380059
2063	0.05	5	0.8	0.5	5	0.5	200	0.674358229	0.358584832
2064	0.05	5	0.8	0.5	7	0.5	200	0.673106981	0.357184155
2065	0.05	5	0.8	0.5	9	0.5	200	0.673486458	0.357683965
2066	0.05	5	0.8	0.5	11	0.5	200	0.673637843	0.358539996
2067	0.05	5	0.8	0.5	13	0.5	200	0.674056233	0.359802243
2068	0.05	5	0.8	0.5	15	0.5	200	0.674624588	0.360910379
2069	0.05	5	0.8	0.5	17	0.5	200	0.675191007	0.361548596
2070	0.05	5	0.8	0.5	19	0.5	200	0.674775716	0.360539185
2071	0.05	5	0.9	0.5	1	0.5	200	0.671136765	0.351945222
2072	0.05	5	0.9	0.5	3	0.5	200	0.67488707	0.36018063
2073	0.05	5	0.9	0.5	5	0.5	200	0.673903599	0.357953574
2074	0.05	5	0.9	0.5	7	0.5	200	0.672539445	0.355286689
2075	0.05	5	0.9	0.5	9	0.5	200	0.672311483	0.355251234
2076	0.05	5	0.9	0.5	11	0.5	200	0.674697763	0.360506486
2077	0.05	5	0.9	0.5	13	0.5	200	0.673523949	0.358537457
2078	0.05	5	0.9	0.5	15	0.5	200	0.673675895	0.358549177
2079	0.05	5	0.9	0.5	17	0.5	200	0.676593814	0.364906828
2080	0.05	5	0.9	0.5	19	0.5	200	0.675456588	0.362311016
2081	0.05	5	1	0.5	1	0.5	200	0.673372219	0.357153267
2082	0.05	5	1	0.5	3	0.5	200	0.672918061	0.355194786
2083	0.05	5	1	0.5	5	0.5	200	0.67223594	0.354768886
2084	0.05	5	1	0.5	7	0.5	200	0.672997262	0.356319523
2085	0.05	5	1	0.5	9	0.5	200	0.672881086	0.356841205
2086	0.05	5	1	0.5	11	0.5	200	0.674321513	0.359547613
2087	0.05	5	1	0.5	13	0.5	200	0.674889137	0.360385568
2088	0.05	5	1	0.5	15	0.5	200	0.674623814	0.360593505
2089	0.05	5	1	0.5	17	0.5	200	0.675192641	0.361667476
2090	0.05	5	1	0.5	19	0.5	200	0.6746242	0.361085856
2091	0.05	6	0	0.5	1	0.5	200	0.669018652	0.343194218
2092	0.05	6	0	0.5	3	0.5	200	0.668675761	0.341864702
2093	0.05	6	0	0.5	5	0.5	200	0.669245108	0.344017348
2094	0.05	6	0	0.5	7	0.5	200	0.668412246	0.34257321
2095	0.05	6	0	0.5	9	0.5	200	0.671479309	0.349960516
2096	0.05	6	0	0.5	11	0.5	200	0.668904198	0.344996766
2097	0.05	6	0	0.5	13	0.5	200	0.669964029	0.347487348
2098	0.05	6	0	0.5	15	0.5	200	0.670683814	0.349514651
2099	0.05	6	0	0.5	17	0.5	200	0.671971737	0.352531123
2100	0.05	6	0	0.5	19	0.5	200	0.670040089	0.348529576

#	eta	max_depth	gamma	colsample_bytree	min_child_weight	subsample	nrounds	Accuracy	Kappa
2101	0.05	6	0.1	0.5	1	0.5	200	0.670002554	0.345265099
2102	0.05	6	0.1	0.5	3	0.5	200	0.670228922	0.345254668
2103	0.05	6	0.1	0.5	5	0.5	200	0.669281823	0.344081518
2104	0.05	6	0.1	0.5	7	0.5	200	0.667575725	0.341623979
2105	0.05	6	0.1	0.5	9	0.5	200	0.666781475	0.339622524
2106	0.05	6	0.1	0.5	11	0.5	200	0.671707445	0.351310284
2107	0.05	6	0.1	0.5	13	0.5	200	0.671438978	0.350927904
2108	0.05	6	0.1	0.5	15	0.5	200	0.671782514	0.35157232
2109	0.05	6	0.1	0.5	17	0.5	200	0.672994852	0.354382702
2110	0.05	6	0.1	0.5	19	0.5	200	0.671631	0.352123584
2111	0.05	6	0.2	0.5	1	0.5	200	0.667954643	0.340345913
2112	0.05	6	0.2	0.5	3	0.5	200	0.669850435	0.344782983
2113	0.05	6	0.2	0.5	5	0.5	200	0.669697241	0.345147759
2114	0.05	6	0.2	0.5	7	0.5	200	0.668715708	0.343341105
2115	0.05	6	0.2	0.5	9	0.5	200	0.669848799	0.346747151
2116	0.05	6	0.2	0.5	11	0.5	200	0.669397743	0.345604687
2117	0.05	6	0.2	0.5	13	0.5	200	0.671253804	0.350036754
2118	0.05	6	0.2	0.5	15	0.5	200	0.672463644	0.352525764
2119	0.05	6	0.2	0.5	17	0.5	200	0.671365588	0.351295051
2120	0.05	6	0.2	0.5	19	0.5	200	0.672655277	0.354283301
2121	0.05	6	0.3	0.5	1	0.5	200	0.670078569	0.344245971
2122	0.05	6	0.3	0.5	3	0.5	200	0.669356288	0.344427699
2123	0.05	6	0.3	0.5	5	0.5	200	0.666249837	0.338318144
2124	0.05	6	0.3	0.5	7	0.5	200	0.668561393	0.3431069
2125	0.05	6	0.3	0.5	9	0.5	200	0.668486669	0.343461812
2126	0.05	6	0.3	0.5	11	0.5	200	0.668373163	0.343663651
2127	0.05	6	0.3	0.5	13	0.5	200	0.668560706	0.345094918
2128	0.05	6	0.3	0.5	15	0.5	200	0.67136447	0.350584311
2129	0.05	6	0.3	0.5	17	0.5	200	0.67174511	0.351632929
2130	0.05	6	0.3	0.5	19	0.5	200	0.671175032	0.351099422
2131	0.05	6	0.4	0.5	1	0.5	200	0.669208131	0.342606519
2132	0.05	6	0.4	0.5	3	0.5	200	0.668450385	0.341864086
2133	0.05	6	0.4	0.5	5	0.5	200	0.667729265	0.340938189
2134	0.05	6	0.4	0.5	7	0.5	200	0.6696975	0.34522805
2135	0.05	6	0.4	0.5	9	0.5	200	0.672047667	0.351000733
2136	0.05	6	0.4	0.5	11	0.5	200	0.670568887	0.349102307
2137	0.05	6	0.4	0.5	13	0.5	200	0.669812944	0.348144188
2138	0.05	6	0.4	0.5	15	0.5	200	0.67341113	0.35432129
2139	0.05	6	0.4	0.5	17	0.5	200	0.673752643	0.355279827
2140	0.05	6	0.4	0.5	19	0.5	200	0.673561658	0.35589263
2141	0.05	6	0.5	0.5	1	0.5	200	0.668107837	0.340657097
2142	0.05	6	0.5	0.5	3	0.5	200	0.668828352	0.342036186
2143	0.05	6	0.5	0.5	5	0.5	200	0.670342128	0.346424383
2144	0.05	6	0.5	0.5	7	0.5	200	0.669812041	0.345448911
2145	0.05	6	0.5	0.5	9	0.5	200	0.66958563	0.345698947
2146	0.05	6	0.5	0.5	11	0.5	200	0.669586748	0.346036549
2147	0.05	6	0.5	0.5	13	0.5	200	0.670381385	0.348515559
2148	0.05	6	0.5	0.5	15	0.5	200	0.669054723	0.346532659
2149	0.05	6	0.5	0.5	17	0.5	200	0.674547754	0.357692656
2150	0.05	6	0.5	0.5	19	0.5	200	0.672012026	0.352209215
2151	0.05	6	0.6	0.5	1	0.5	200	0.669055842	0.343233303
2152	0.05	6	0.6	0.5	3	0.5	200	0.671061481	0.347697999
2153	0.05	6	0.6	0.5	5	0.5	200	0.670004404	0.345976715
2154	0.05	6	0.6	0.5	7	0.5	200	0.667424125	0.341507863
2155	0.05	6	0.6	0.5	9	0.5	200	0.670116191	0.346983117
2156	0.05	6	0.6	0.5	11	0.5	200	0.670381128	0.347994407
2157	0.05	6	0.6	0.5	13	0.5	200	0.671554209	0.350789556
2158	0.05	6	0.6	0.5	15	0.5	200	0.671135905	0.350735769
2159	0.05	6	0.6	0.5	17	0.5	200	0.671743818	0.352247442
2160	0.05	6	0.6	0.5	19	0.5	200	0.672881775	0.354539428
2161	0.05	6	0.7	0.5	1	0.5	200	0.668071078	0.341048297
2162	0.05	6	0.7	0.5	3	0.5	200	0.672125748	0.349230031
2163	0.05	6	0.7	0.5	5	0.5	200	0.669849833	0.346172391
2164	0.05	6	0.7	0.5	7	0.5	200	0.669055152	0.344428541
2165	0.05	6	0.7	0.5	9	0.5	200	0.66954792	0.345732397
2166	0.05	6	0.7	0.5	11	0.5	200	0.669019469	0.345616692
2167	0.05	6	0.7	0.5	13	0.5	200	0.67049541	0.348956874
2168	0.05	6	0.7	0.5	15	0.5	200	0.672577884	0.35282136
2169	0.05	6	0.7	0.5	17	0.5	200	0.67151917	0.351987759
2170	0.05	6	0.7	0.5	19	0.5	200	0.672351816	0.353448892
2171	0.05	6	0.8	0.5	1	0.5	200	0.668334852	0.341477379
2172	0.05	6	0.8	0.5	3	0.5	200	0.669131085	0.343447594
2173	0.05	6	0.8	0.5	5	0.5	200	0.667879619	0.341816891
2174	0.05	6	0.8	0.5	7	0.5	200	0.670685406	0.347705288
2175	0.05	6	0.8	0.5	9	0.5	200	0.670077322	0.346895575
2176	0.05	6	0.8	0.5	11	0.5	200	0.670835499	0.348763442
2177	0.05	6	0.8	0.5	13	0.5	200	0.671213558	0.350528402
2178	0.05	6	0.8	0.5	15	0.5	200	0.671063851	0.350312138
2179	0.05	6	0.8	0.5	17	0.5	200	0.673525283	0.355898088
2180	0.05	6	0.8	0.5	19	0.5	200	0.672122822	0.353171184
2181	0.05	6	0.9	0.5	1	0.5	200	0.668903465	0.342461049
2182	0.05	6	0.9	0.5	3	0.5	200	0.670040603	0.345200977
2183	0.05	6	0.9	0.5	5	0.5	200	0.670493085	0.346575924
2184	0.05	6	0.9	0.5	7	0.5	200	0.668865286	0.344496403
2185	0.05	6	0.9	0.5	9	0.5	200	0.665987269	0.338725354
2186	0.05	6	0.9	0.5	11	0.5	200	0.669887971	0.346294179
2187	0.05	6	0.9	0.5	13	0.5	200	0.670080421	0.348414963
2188	0.05	6	0.9	0.5	15	0.5	200	0.673525284	0.355530456
2189	0.05	6	0.9	0.5	17	0.5	200	0.671518051	0.351483581
2190	0.05	6	0.9	0.5	19	0.5	200	0.674093855	0.356819806
2191	0.05	6	1	0.5	1	0.5	200	0.668827535	0.343980733
2192	0.05	6	1	0.5	3	0.5	200	0.672275628	0.349623839
2193	0.05	6	1	0.5	5	0.5	200	0.670228406	0.346763044
2194	0.05	6	1	0.5	7	0.5	200	0.669737617	0.345386142
2195	0.05	6	1	0.5	9	0.5	200	0.670381041	0.348442151
2196	0.05	6	1	0.5	11	0.5	200	0.668525109	0.344508066
2197	0.05	6	1	0.5	13	0.5	200	0.670077407	0.348465095
2198	0.05	6	1	0.5	15	0.5	200	0.668599059	0.34588365
2199	0.05	6	1	0.5	17	0.5	200	0.672464978	0.353708832
2200	0.05	6	1	0.5	19	0.5	200	0.672389179	0.354013545
2201	0.05	7	0	0.5	1	0.5	200	0.665910264	0.332351693
2202	0.05	7	0	0.5	3	0.5	200	0.665267358	0.331783678
2203	0.05	7	0	0.5	5	0.5	200	0.669586574	0.341427172
2204	0.05	7	0	0.5	7	0.5	200	0.666859259	0.336659633
2205	0.05	7	0	0.5	9	0.5	200	0.664697453	0.332582878
2206	0.05	7	0	0.5	11	0.5	200	0.666100864	0.336611683
2207	0.05	7	0	0.5	13	0.5	200	0.66810629	0.34144654
2208	0.05	7	0	0.5	15	0.5	200	0.66886507	0.342946784
2209	0.05	7	0	0.5	17	0.5	200	0.669548267	0.34535403
2210	0.05	7	0	0.5	19	0.5	200	0.671329819	0.349104982
2211	0.05	7	0.1	0.5	1	0.5	200	0.667694096	0.336583326
2212	0.05	7	0.1	0.5	3	0.5	200	0.666439965	0.33361153
2213	0.05	7	0.1	0.5	5	0.5	200	0.669359822	0.340529886
2214	0.05	7	0.1	0.5	7	0.5	200	0.669813331	0.342630528
2215	0.05	7	0.1	0.5	9	0.5	200	0.670571983	0.344638745
2216	0.05	7	0.1	0.5	11	0.5	200	0.665949176	0.335983834
2217	0.05	7	0.1	0.5	13	0.5	200	0.667843893	0.340613777
2218	0.05	7	0.1	0.5	15	0.5	200	0.669663625	0.344856412
2219	0.05	7	0.1	0.5	17	0.5	200	0.670721778	0.347319488
2220	0.05	7	0.1	0.5	19	0.5	200	0.670154802	0.346152612
2221	0.05	7	0.2	0.5	1	0.5	200	0.665986798	0.332465746
2222	0.05	7	0.2	0.5	3	0.5	200	0.664132842	0.329523148
2223	0.05	7	0.2	0.5	5	0.5	200	0.669055194	0.339816005
2224	0.05	7	0.2	0.5	7	0.5	200	0.666213165	0.335392057
2225	0.05	7	0.2	0.5	9	0.5	200	0.667310488	0.33832527
2226	0.05	7	0.2	0.5	11	0.5	200	0.667123336	0.338882462
2227	0.05	7	0.2	0.5	13	0.5	200	0.668411427	0.341653987
2228	0.05	7	0.2	0.5	15	0.5	200	0.669888961	0.345552968
2229	0.05	7	0.2	0.5	17	0.5	200	0.668523603	0.342712743
2230	0.05	7	0.2	0.5	19	0.5	200	0.669776101	0.345749344
2231	0.05	7	0.3	0.5	1	0.5	200	0.665989119	0.331968865
2232	0.05	7	0.3	0.5	3	0.5	200	0.665116486	0.331148553
2233	0.05	7	0.3	0.5	5	0.5	200	0.667389775	0.337361749
2234	0.05	7	0.3	0.5	7	0.5	200	0.664774158	0.331700591
2235	0.05	7	0.3	0.5	9	0.5	200	0.666555366	0.33706978
2236	0.05	7	0.3	0.5	11	0.5	200	0.668335284	0.340961689
2237	0.05	7	0.3	0.5	13	0.5	200	0.667654457	0.340365095
2238	0.05	7	0.3	0.5	15	0.5	200	0.668336746	0.34216885
2239	0.05	7	0.3	0.5	17	0.5	200	0.668299988	0.343122259
2240	0.05	7	0.3	0.5	19	0.5	200	0.671744378	0.350632968
2241	0.05	7	0.4	0.5	1	0.5	200	0.664737012	0.330299701
2242	0.05	7	0.4	0.5	3	0.5	200	0.666898127	0.335067594
2243	0.05	7	0.4	0.5	5	0.5	200	0.666859431	0.335513978
2244	0.05	7	0.4	0.5	7	0.5	200	0.668942335	0.340565195
2245	0.05	7	0.4	0.5	9	0.5	200	0.667805539	0.339075095
2246	0.05	7	0.4	0.5	11	0.5	200	0.670305843	0.345099719
2247	0.05	7	0.4	0.5	13	0.5	200	0.66693536	0.339235596
2248	0.05	7	0.4	0.5	15	0.5	200	0.669698963	0.344981385
2249	0.05	7	0.4	0.5	17	0.5	200	0.671706972	0.349630546
2250	0.05	7	0.4	0.5	19	0.5	200	0.67091113	0.348335099
2251	0.05	7	0.5	0.5	1	0.5	200	0.664435745	0.328848553
2252	0.05	7	0.5	0.5	3	0.5	200	0.666329513	0.333767499
2253	0.05	7	0.5	0.5	5	0.5	200	0.666933767	0.335424153
2254	0.05	7	0.5	0.5	7	0.5	200	0.668944099	0.341822752
2255	0.05	7	0.5	0.5	9	0.5	200	0.665684582	0.334716762
2256	0.05	7	0.5	0.5	11	0.5	200	0.66822083	0.340478485
2257	0.05	7	0.5	0.5	13	0.5	200	0.667085281	0.339244444
2258	0.05	7	0.5	0.5	15	0.5	200	0.669208392	0.344748459
2259	0.05	7	0.5	0.5	17	0.5	200	0.671782816	0.349797569
2260	0.05	7	0.5	0.5	19	0.5	200	0.670077539	0.347211653
2261	0.05	7	0.6	0.5	1	0.5	200	0.664661513	0.329332515
2262	0.05	7	0.6	0.5	3	0.5	200	0.667804721	0.337081269
2263	0.05	7	0.6	0.5	5	0.5	200	0.66621493	0.333853373
2264	0.05	7	0.6	0.5	7	0.5	200	0.667729051	0.338782902
2265	0.05	7	0.6	0.5	9	0.5	200	0.665342685	0.333991642
2266	0.05	7	0.6	0.5	11	0.5	200	0.668864769	0.341970715
2267	0.05	7	0.6	0.5	13	0.5	200	0.669094712	0.342839951
2268	0.05	7	0.6	0.5	15	0.5	200	0.666896018	0.339696669
2269	0.05	7	0.6	0.5	17	0.5	200	0.670986715	0.348892594
2270	0.05	7	0.6	0.5	19	0.5	200	0.669357625	0.345636312
2271	0.05	7	0.7	0.5	1	0.5	200	0.663678556	0.327603121
2272	0.05	7	0.7	0.5	3	0.5	200	0.668487187	0.337896933
2273	0.05	7	0.7	0.5	5	0.5	200	0.667161169	0.337095397
2274	0.05	7	0.7	0.5	7	0.5	200	0.666896706	0.336492932
2275	0.05	7	0.7	0.5	9	0.5	200	0.667957312	0.340143085
2276	0.05	7	0.7	0.5	11	0.5	200	0.669583693	0.343412465
2277	0.05	7	0.7	0.5	13	0.5	200	0.66666952	0.338495304
2278	0.05	7	0.7	0.5	15	0.5	200	0.670720917	0.347620594
2279	0.05	7	0.7	0.5	17	0.5	200	0.669398387	0.344789774
2280	0.05	7	0.7	0.5	19	0.5	200	0.670495279	0.347312606
2281	0.05	7	0.8	0.5	1	0.5	200	0.66685887	0.334334215
2282	0.05	7	0.8	0.5	3	0.5	200	0.666593288	0.334308443
2283	0.05	7	0.8	0.5	5	0.5	200	0.668221689	0.338106114
2284	0.05	7	0.8	0.5	7	0.5	200	0.667200857	0.337325191
2285	0.05	7	0.8	0.5	9	0.5	200	0.666632803	0.336934902
2286	0.05	7	0.8	0.5	11	0.5	200	0.665647868	0.335991342
2287	0.05	7	0.8	0.5	13	0.5	200	0.666289526	0.337880804
2288	0.05	7	0.8	0.5	15	0.5	200	0.668523945	0.343043752
2289	0.05	7	0.8	0.5	17	0.5	200	0.671063678	0.348569068
2290	0.05	7	0.8	0.5	19	0.5	200	0.670456799	0.347778291
2291	0.05	7	0.9	0.5	1	0.5	200	0.664472118	0.329741394
2292	0.05	7	0.9	0.5	3	0.5	200	0.665610375	0.33283246
2293	0.05	7	0.9	0.5	5	0.5	200	0.665910908	0.333651324
2294	0.05	7	0.9	0.5	7	0.5	200	0.667768779	0.338656985
2295	0.05	7	0.9	0.5	9	0.5	200	0.668826546	0.341466596
2296	0.05	7	0.9	0.5	11	0.5	200	0.667994374	0.340385161
2297	0.05	7	0.9	0.5	13	0.5	200	0.671176928	0.348092954
2298	0.05	7	0.9	0.5	15	0.5	200	0.669623594	0.345001504
2299	0.05	7	0.9	0.5	17	0.5	200	0.669359088	0.345263585
2300	0.05	7	0.9	0.5	19	0.5	200	0.67269208	0.352598637
2301	0.05	7	1	0.5	1	0.5	200	0.666896404	0.334554663
2302	0.05	7	1	0.5	3	0.5	200	0.665947971	0.333084227
2303	0.05	7	1	0.5	5	0.5	200	0.668181487	0.338822621
2304	0.05	7	1	0.5	7	0.5	200	0.666630994	0.335873477
2305	0.05	7	1	0.5	9	0.5	200	0.667086099	0.337177556
2306	0.05	7	1	0.5	11	0.5	200	0.667161859	0.338702714
2307	0.05	7	1	0.5	13	0.5	200	0.67068265	0.34654045
2308	0.05	7	1	0.5	15	0.5	200	0.668789357	0.343069928
2309	0.05	7	1	0.5	17	0.5	200	0.669926108	0.346233946
2310	0.05	7	1	0.5	19	0.5	200	0.671971607	0.350737388
2311	0.05	8	0	0.5	1	0.5	200	0.664814621	0.326713332
2312	0.05	8	0	0.5	3	0.5	200	0.66602601	0.330112781
2313	0.05	8	0	0.5	5	0.5	200	0.663752763	0.326516535
2314	0.05	8	0	0.5	7	0.5	200	0.66348559	0.326186912
2315	0.05	8	0	0.5	9	0.5	200	0.662804932	0.326374103
2316	0.05	8	0	0.5	11	0.5	200	0.665608955	0.333578797
2317	0.05	8	0	0.5	13	0.5	200	0.667010128	0.336892926
2318	0.05	8	0	0.5	15	0.5	200	0.666554463	0.337491488
2319	0.05	8	0	0.5	17	0.5	200	0.669736756	0.344348864
2320	0.05	8	0	0.5	19	0.5	200	0.669891287	0.345582973
2321	0.05	8	0.1	0.5	1	0.5	200	0.659282244	0.314761838
2322	0.05	8	0.1	0.5	3	0.5	200	0.663713336	0.325045263
2323	0.05	8	0.1	0.5	5	0.5	200	0.664926836	0.328869163
2324	0.05	8	0.1	0.5	7	0.5	200	0.66458399	0.329253524
2325	0.05	8	0.1	0.5	9	0.5	200	0.662954983	0.32737693
2326	0.05	8	0.1	0.5	11	0.5	200	0.666896834	0.335981814
2327	0.05	8	0.1	0.5	13	0.5	200	0.66629155	0.335713992
2328	0.05	8	0.1	0.5	15	0.5	200	0.670609347	0.345061219
2329	0.05	8	0.1	0.5	17	0.5	200	0.670648346	0.345967725
2330	0.05	8	0.1	0.5	19	0.5	200	0.670684589	0.346577072
2331	0.05	8	0.2	0.5	1	0.5	200	0.662389385	0.321890759
2332	0.05	8	0.2	0.5	3	0.5	200	0.66454809	0.327245205
2333	0.05	8	0.2	0.5	5	0.5	200	0.663563715	0.326289547
2334	0.05	8	0.2	0.5	7	0.5	200	0.66507749	0.330612681
2335	0.05	8	0.2	0.5	9	0.5	200	0.664774115	0.33112394
2336	0.05	8	0.2	0.5	11	0.5	200	0.66341164	0.329180812
2337	0.05	8	0.2	0.5	13	0.5	200	0.665948917	0.334590589
2338	0.05	8	0.2	0.5	15	0.5	200	0.668865156	0.342260363
2339	0.05	8	0.2	0.5	17	0.5	200	0.670761379	0.345544179
2340	0.05	8	0.2	0.5	19	0.5	200	0.668904498	0.34317611
2341	0.05	8	0.3	0.5	1	0.5	200	0.660418438	0.317387108
2342	0.05	8	0.3	0.5	3	0.5	200	0.661971901	0.321023842
2343	0.05	8	0.3	0.5	5	0.5	200	0.667881125	0.334102457
2344	0.05	8	0.3	0.5	7	0.5	200	0.664206752	0.327932485
2345	0.05	8	0.3	0.5	9	0.5	200	0.667008622	0.335165956
2346	0.05	8	0.3	0.5	11	0.5	200	0.6687897	0.339836595
2347	0.05	8	0.3	0.5	13	0.5	200	0.669662807	0.342375992
2348	0.05	8	0.3	0.5	15	0.5	200	0.667502896	0.338872146
2349	0.05	8	0.3	0.5	17	0.5	200	0.671365417	0.347399398
2350	0.05	8	0.3	0.5	19	0.5	200	0.669170168	0.343879746
2351	0.05	8	0.4	0.5	1	0.5	200	0.660872639	0.318479011
2352	0.05	8	0.4	0.5	3	0.5	200	0.664546411	0.327070058
2353	0.05	8	0.4	0.5	5	0.5	200	0.664584849	0.328625238
2354	0.05	8	0.4	0.5	7	0.5	200	0.665949736	0.33251574
2355	0.05	8	0.4	0.5	9	0.5	200	0.666290085	0.33302586
2356	0.05	8	0.4	0.5	11	0.5	200	0.667807089	0.337198585
2357	0.05	8	0.4	0.5	13	0.5	200	0.667693409	0.338878737
2358	0.05	8	0.4	0.5	15	0.5	200	0.667539399	0.339262262
2359	0.05	8	0.4	0.5	17	0.5	200	0.669169609	0.342463119
2360	0.05	8	0.4	0.5	19	0.5	200	0.670229051	0.346294241
2361	0.05	8	0.5	0.5	1	0.5	200	0.665533326	0.32847175
2362	0.05	8	0.5	0.5	3	0.5	200	0.663221256	0.324460227
2363	0.05	8	0.5	0.5	5	0.5	200	0.664245576	0.32754452
2364	0.05	8	0.5	0.5	7	0.5	200	0.666706967	0.333708927
2365	0.05	8	0.5	0.5	9	0.5	200	0.663336959	0.326818908
2366	0.05	8	0.5	0.5	11	0.5	200	0.668108484	0.338570633
2367	0.05	8	0.5	0.5	13	0.5	200	0.66799644	0.338999364
2368	0.05	8	0.5	0.5	15	0.5	200	0.668563158	0.340940085
2369	0.05	8	0.5	0.5	17	0.5	200	0.667882588	0.340517445
2370	0.05	8	0.5	0.5	19	0.5	200	0.671138188	0.347284731
2371	0.05	8	0.6	0.5	1	0.5	200	0.663031774	0.323277927
2372	0.05	8	0.6	0.5	3	0.5	200	0.665870878	0.33036345
2373	0.05	8	0.6	0.5	5	0.5	200	0.663563198	0.32631252
2374	0.05	8	0.6	0.5	7	0.5	200	0.665419218	0.331424708
2375	0.05	8	0.6	0.5	9	0.5	200	0.667881598	0.336079703
2376	0.05	8	0.6	0.5	11	0.5	200	0.666480599	0.335130479
2377	0.05	8	0.6	0.5	13	0.5	200	0.663714068	0.33055333
2378	0.05	8	0.6	0.5	15	0.5	200	0.667351596	0.339490777
2379	0.05	8	0.6	0.5	17	0.5	200	0.669699393	0.343967218
2380	0.05	8	0.6	0.5	19	0.5	200	0.67102567	0.347526668
2381	0.05	8	0.7	0.5	1	0.5	200	0.663864592	0.324909508
2382	0.05	8	0.7	0.5	3	0.5	200	0.664963982	0.327107274
2383	0.05	8	0.7	0.5	5	0.5	200	0.664243682	0.326884814
2384	0.05	8	0.7	0.5	7	0.5	200	0.663790214	0.328710311
2385	0.05	8	0.7	0.5	9	0.5	200	0.665456537	0.332753136
2386	0.05	8	0.7	0.5	11	0.5	200	0.665606372	0.333238982
2387	0.05	8	0.7	0.5	13	0.5	200	0.665761504	0.335073429
2388	0.05	8	0.7	0.5	15	0.5	200	0.667994934	0.340092723
2389	0.05	8	0.7	0.5	17	0.5	200	0.667501175	0.339364723
2390	0.05	8	0.7	0.5	19	0.5	200	0.671025066	0.347513293
2391	0.05	8	0.8	0.5	1	0.5	200	0.664663018	0.326174962
2392	0.05	8	0.8	0.5	3	0.5	200	0.665718718	0.329027579
2393	0.05	8	0.8	0.5	5	0.5	200	0.66526697	0.329565178
2394	0.05	8	0.8	0.5	7	0.5	200	0.663673562	0.327608856
2395	0.05	8	0.8	0.5	9	0.5	200	0.665721472	0.333179626
2396	0.05	8	0.8	0.5	11	0.5	200	0.666781865	0.336004758
2397	0.05	8	0.8	0.5	13	0.5	200	0.668487918	0.339915464
2398	0.05	8	0.8	0.5	15	0.5	200	0.669320908	0.342607984
2399	0.05	8	0.8	0.5	17	0.5	200	0.669588513	0.344669711
2400	0.05	8	0.8	0.5	19	0.5	200	0.669737231	0.345362712

#	eta	max_depth	gamma	colsample_bytree	min_child_weight	subsample	nrounds	Accuracy	Kappa
2401	0.05	8	0.9	0.5	1	0.5	200	0.662200765	0.320754613
2402	0.05	8	0.9	0.5	3	0.5	200	0.663523682	0.325405816
2403	0.05	8	0.9	0.5	5	0.5	200	0.663977627	0.326886417
2404	0.05	8	0.9	0.5	7	0.5	200	0.663713637	0.327915124
2405	0.05	8	0.9	0.5	9	0.5	200	0.666707356	0.334453421
2406	0.05	8	0.9	0.5	11	0.5	200	0.667957528	0.338549439
2407	0.05	8	0.9	0.5	13	0.5	200	0.66689804	0.336892352
2408	0.05	8	0.9	0.5	15	0.5	200	0.666252594	0.336345492
2409	0.05	8	0.9	0.5	17	0.5	200	0.670343722	0.346577547
2410	0.05	8	0.9	0.5	19	0.5	200	0.667350993	0.340914135
2411	0.05	8	1	0.5	1	0.5	200	0.664470783	0.327054341
2412	0.05	8	1	0.5	3	0.5	200	0.661554157	0.321723847
2413	0.05	8	1	0.5	5	0.5	200	0.664357018	0.327852365
2414	0.05	8	1	0.5	7	0.5	200	0.665949392	0.332572763
2415	0.05	8	1	0.5	9	0.5	200	0.666932776	0.335649385
2416	0.05	8	1	0.5	11	0.5	200	0.665265076	0.333085796
2417	0.05	8	1	0.5	13	0.5	200	0.664320559	0.331825447
2418	0.05	8	1	0.5	15	0.5	200	0.668411558	0.340517171
2419	0.05	8	1	0.5	17	0.5	200	0.6694345	0.344508925
2420	0.05	8	1	0.5	19	0.5	200	0.668903982	0.343419305
2421	0.05	9	0	0.5	1	0.5	200	0.662161251	0.318757566
2422	0.05	9	0	0.5	3	0.5	200	0.660835922	0.316047586
2423	0.05	9	0	0.5	5	0.5	200	0.661176574	0.318425644
2424	0.05	9	0	0.5	7	0.5	200	0.661934537	0.322012338
2425	0.05	9	0	0.5	9	0.5	200	0.665305236	0.329792276
2426	0.05	9	0	0.5	11	0.5	200	0.663903246	0.32900506
2427	0.05	9	0	0.5	13	0.5	200	0.664470826	0.330950943
2428	0.05	9	0	0.5	15	0.5	200	0.668297018	0.339374913
2429	0.05	9	0	0.5	17	0.5	200	0.666594106	0.335857875
2430	0.05	9	0	0.5	19	0.5	200	0.668562471	0.341810408
2431	0.05	9	0.1	0.5	1	0.5	200	0.661595479	0.317285791
2432	0.05	9	0.1	0.5	3	0.5	200	0.660721686	0.316682149
2433	0.05	9	0.1	0.5	5	0.5	200	0.66219741	0.320169705
2434	0.05	9	0.1	0.5	7	0.5	200	0.664282551	0.326210079
2435	0.05	9	0.1	0.5	9	0.5	200	0.664280271	0.327798464
2436	0.05	9	0.1	0.5	11	0.5	200	0.663829771	0.328177185
2437	0.05	9	0.1	0.5	13	0.5	200	0.665117477	0.332116865
2438	0.05	9	0.1	0.5	15	0.5	200	0.668524634	0.339497863
2439	0.05	9	0.1	0.5	17	0.5	200	0.66594866	0.335899397
2440	0.05	9	0.1	0.5	19	0.5	200	0.6689045	0.341695781
2441	0.05	9	0.2	0.5	1	0.5	200	0.660911207	0.315658592
2442	0.05	9	0.2	0.5	3	0.5	200	0.663637665	0.322247408
2443	0.05	9	0.2	0.5	5	0.5	200	0.664739981	0.325745361
2444	0.05	9	0.2	0.5	7	0.5	200	0.666442892	0.331203911
2445	0.05	9	0.2	0.5	9	0.5	200	0.664660695	0.329311521
2446	0.05	9	0.2	0.5	11	0.5	200	0.664055793	0.329570164
2447	0.05	9	0.2	0.5	13	0.5	200	0.667274074	0.336587008
2448	0.05	9	0.2	0.5	15	0.5	200	0.666137451	0.334718829
2449	0.05	9	0.2	0.5	17	0.5	200	0.667766757	0.338861216
2450	0.05	9	0.2	0.5	19	0.5	200	0.669509398	0.34276382
2451	0.05	9	0.3	0.5	1	0.5	200	0.66011674	0.314108232
2452	0.05	9	0.3	0.5	3	0.5	200	0.661742173	0.318821471
2453	0.05	9	0.3	0.5	5	0.5	200	0.66371325	0.324044258
2454	0.05	9	0.3	0.5	7	0.5	200	0.663980381	0.326114941
2455	0.05	9	0.3	0.5	9	0.5	200	0.663036037	0.32561086
2456	0.05	9	0.3	0.5	11	0.5	200	0.665226596	0.331627734
2457	0.05	9	0.3	0.5	13	0.5	200	0.665001732	0.331789439
2458	0.05	9	0.3	0.5	15	0.5	200	0.668335325	0.339542763
2459	0.05	9	0.3	0.5	17	0.5	200	0.667994675	0.339941458
2460	0.05	9	0.3	0.5	19	0.5	200	0.669169348	0.342742823
2461	0.05	9	0.4	0.5	1	0.5	200	0.658901822	0.311742108
2462	0.05	9	0.4	0.5	3	0.5	200	0.662463809	0.320257208
2463	0.05	9	0.4	0.5	5	0.5	200	0.664851205	0.326480129
2464	0.05	9	0.4	0.5	7	0.5	200	0.663638094	0.325104858
2465	0.05	9	0.4	0.5	9	0.5	200	0.663676018	0.326383275
2466	0.05	9	0.4	0.5	11	0.5	200	0.665494371	0.331677894
2467	0.05	9	0.4	0.5	13	0.5	200	0.667881597	0.337495006
2468	0.05	9	0.4	0.5	15	0.5	200	0.667198145	0.337250173
2469	0.05	9	0.4	0.5	17	0.5	200	0.665342168	0.334189981
2470	0.05	9	0.4	0.5	19	0.5	200	0.668335197	0.341396244
2471	0.05	9	0.5	0.5	1	0.5	200	0.659924508	0.313993647
2472	0.05	9	0.5	0.5	3	0.5	200	0.661594275	0.318607113
2473	0.05	9	0.5	0.5	5	0.5	200	0.661025703	0.318884805
2474	0.05	9	0.5	0.5	7	0.5	200	0.665456665	0.328703282
2475	0.05	9	0.5	0.5	9	0.5	200	0.665608869	0.33114405
2476	0.05	9	0.5	0.5	11	0.5	200	0.662198011	0.325235241
2477	0.05	9	0.5	0.5	13	0.5	200	0.668450384	0.339027118
2478	0.05	9	0.5	0.5	15	0.5	200	0.66632736	0.335647653
2479	0.05	9	0.5	0.5	17	0.5	200	0.668070864	0.33957044
2480	0.05	9	0.5	0.5	19	0.5	200	0.667843633	0.340163143
2481	0.05	9	0.6	0.5	1	0.5	200	0.661022605	0.315694077
2482	0.05	9	0.6	0.5	3	0.5	200	0.664284875	0.324098895
2483	0.05	9	0.6	0.5	5	0.5	200	0.66015221	0.316944899
2484	0.05	9	0.6	0.5	7	0.5	200	0.663978962	0.326171118
2485	0.05	9	0.6	0.5	9	0.5	200	0.665116057	0.329348484
2486	0.05	9	0.6	0.5	11	0.5	200	0.664018476	0.329686165
2487	0.05	9	0.6	0.5	13	0.5	200	0.666708991	0.335510917
2488	0.05	9	0.6	0.5	15	0.5	200	0.667840706	0.338729557
2489	0.05	9	0.6	0.5	17	0.5	200	0.667351771	0.338679663
2490	0.05	9	0.6	0.5	19	0.5	200	0.669321208	0.343714311
2491	0.05	9	0.7	0.5	1	0.5	200	0.658905525	0.312196996
2492	0.05	9	0.7	0.5	3	0.5	200	0.66374988	0.322657071
2493	0.05	9	0.7	0.5	5	0.5	200	0.663867735	0.324832535
2494	0.05	9	0.7	0.5	7	0.5	200	0.663637148	0.325608263
2495	0.05	9	0.7	0.5	9	0.5	200	0.664359039	0.32757251
2496	0.05	9	0.7	0.5	11	0.5	200	0.664283756	0.328940403
2497	0.05	9	0.7	0.5	13	0.5	200	0.666176492	0.335057163
2498	0.05	9	0.7	0.5	15	0.5	200	0.666363519	0.335534446
2499	0.05	9	0.7	0.5	17	0.5	200	0.668941818	0.342064464
2500	0.05	9	0.7	0.5	19	0.5	200	0.668753501	0.343351809
2501	0.05	9	0.8	0.5	1	0.5	200	0.660379827	0.31511533
2502	0.05	9	0.8	0.5	3	0.5	200	0.661250568	0.318119178
2503	0.05	9	0.8	0.5	5	0.5	200	0.664056011	0.325323646
2504	0.05	9	0.8	0.5	7	0.5	200	0.665684198	0.329932137
2505	0.05	9	0.8	0.5	9	0.5	200	0.664736968	0.329284053
2506	0.05	9	0.8	0.5	11	0.5	200	0.665759267	0.332431354
2507	0.05	9	0.8	0.5	13	0.5	200	0.667010344	0.336091829
2508	0.05	9	0.8	0.5	15	0.5	200	0.666364767	0.336037882
2509	0.05	9	0.8	0.5	17	0.5	200	0.668145976	0.340581491
2510	0.05	9	0.8	0.5	19	0.5	200	0.668601168	0.341999845
2511	0.05	9	0.9	0.5	1	0.5	200	0.663034272	0.320984789
2512	0.05	9	0.9	0.5	3	0.5	200	0.663257887	0.32184286
2513	0.05	9	0.9	0.5	5	0.5	200	0.664434497	0.326209376
2514	0.05	9	0.9	0.5	7	0.5	200	0.664547445	0.327584675
2515	0.05	9	0.9	0.5	9	0.5	200	0.666177052	0.331733378
2516	0.05	9	0.9	0.5	11	0.5	200	0.664282421	0.329884049
2517	0.05	9	0.9	0.5	13	0.5	200	0.666707011	0.335538035
2518	0.05	9	0.9	0.5	15	0.5	200	0.667124711	0.337501684
2519	0.05	9	0.9	0.5	17	0.5	200	0.667200126	0.338144782
2520	0.05	9	0.9	0.5	19	0.5	200	0.669851383	0.344939407
2521	0.05	9	1	0.5	1	0.5	200	0.662386629	0.319588504
2522	0.05	9	1	0.5	3	0.5	200	0.664963123	0.324750587
2523	0.05	9	1	0.5	5	0.5	200	0.659924376	0.316921743
2524	0.05	9	1	0.5	7	0.5	200	0.663299208	0.326168027
2525	0.05	9	1	0.5	9	0.5	200	0.665305019	0.330622711
2526	0.05	9	1	0.5	11	0.5	200	0.665647352	0.332606743
2527	0.05	9	1	0.5	13	0.5	200	0.665722462	0.334364063
2528	0.05	9	1	0.5	15	0.5	200	0.664889043	0.332851507
2529	0.05	9	1	0.5	17	0.5	200	0.668828828	0.341773811
2530	0.05	9	1	0.5	19	0.5	200	0.668525841	0.341601688
2531	0.05	10	0	0.5	1	0.5	200	0.659168438	0.310152798
2532	0.05	10	0	0.5	3	0.5	200	0.659698697	0.312884319
2533	0.05	10	0	0.5	5	0.5	200	0.658601806	0.31148019
2534	0.05	10	0	0.5	7	0.5	200	0.663676879	0.324042755
2535	0.05	10	0	0.5	9	0.5	200	0.66363818	0.325796122
2536	0.05	10	0	0.5	11	0.5	200	0.663104994	0.325660039
2537	0.05	10	0	0.5	13	0.5	200	0.665001216	0.330813468
2538	0.05	10	0	0.5	15	0.5	200	0.664319225	0.329967755
2539	0.05	10	0	0.5	17	0.5	200	0.665948573	0.335473509
2540	0.05	10	0	0.5	19	0.5	200	0.668488692	0.341304353
2541	0.05	10	0.1	0.5	1	0.5	200	0.658297699	0.308924096
2542	0.05	10	0.1	0.5	3	0.5	200	0.660155095	0.313962476
2543	0.05	10	0.1	0.5	5	0.5	200	0.660832176	0.31631062
2544	0.05	10	0.1	0.5	7	0.5	200	0.661363601	0.319617957
2545	0.05	10	0.1	0.5	9	0.5	200	0.66223602	0.323719228
2546	0.05	10	0.1	0.5	11	0.5	200	0.664393992	0.328522339
2547	0.05	10	0.1	0.5	13	0.5	200	0.665723108	0.332764941
2548	0.05	10	0.1	0.5	15	0.5	200	0.664624407	0.330341737
2549	0.05	10	0.1	0.5	17	0.5	200	0.667879833	0.339192387
2550	0.05	10	0.1	0.5	19	0.5	200	0.666555541	0.337308863

#	eta	max_depth	gamma	colsample_bytree	min_child_weight	subsample	nrounds	Accuracy	Kappa
2551	0.05	10	0.2	0.5	1	0.5	200	0.658637445	0.309540247
2552	0.05	10	0.2	0.5	3	0.5	200	0.661592124	0.316452864
2553	0.05	10	0.2	0.5	5	0.5	200	0.66193243	0.318325665
2554	0.05	10	0.2	0.5	7	0.5	200	0.662464929	0.32162279
2555	0.05	10	0.2	0.5	9	0.5	200	0.663335453	0.325167232
2556	0.05	10	0.2	0.5	11	0.5	200	0.663373028	0.32647753
2557	0.05	10	0.2	0.5	13	0.5	200	0.666555927	0.334252222
2558	0.05	10	0.2	0.5	15	0.5	200	0.666555109	0.335279209
2559	0.05	10	0.2	0.5	17	0.5	200	0.666061263	0.334788926
2560	0.05	10	0.2	0.5	19	0.5	200	0.668564406	0.341365748
2561	0.05	10	0.3	0.5	1	0.5	200	0.657843925	0.307666122
2562	0.05	10	0.3	0.5	3	0.5	200	0.661405266	0.316106715
2563	0.05	10	0.3	0.5	5	0.5	200	0.662501686	0.320380649
2564	0.05	10	0.3	0.5	7	0.5	200	0.664015979	0.324516912
2565	0.05	10	0.3	0.5	9	0.5	200	0.665608139	0.329845085
2566	0.05	10	0.3	0.5	11	0.5	200	0.662539351	0.324574427
2567	0.05	10	0.3	0.5	13	0.5	200	0.666592986	0.334453583
2568	0.05	10	0.3	0.5	15	0.5	200	0.665683982	0.333613438
2569	0.05	10	0.3	0.5	17	0.5	200	0.666327361	0.335622047
2570	0.05	10	0.3	0.5	19	0.5	200	0.668791078	0.341216588
2571	0.05	10	0.4	0.5	1	0.5	200	0.657047698	0.30595522
2572	0.05	10	0.4	0.5	3	0.5	200	0.661177348	0.315750584
2573	0.05	10	0.4	0.5	5	0.5	200	0.661328261	0.318528543
2574	0.05	10	0.4	0.5	7	0.5	200	0.66223714	0.320869824
2575	0.05	10	0.4	0.5	9	0.5	200	0.662841906	0.324292781
2576	0.05	10	0.4	0.5	11	0.5	200	0.661857445	0.323427566
2577	0.05	10	0.4	0.5	13	0.5	200	0.663788749	0.328375273
2578	0.05	10	0.4	0.5	15	0.5	200	0.665947454	0.333476858
2579	0.05	10	0.4	0.5	17	0.5	200	0.667125141	0.337373809
2580	0.05	10	0.4	0.5	19	0.5	200	0.670951979	0.345845249
2581	0.05	10	0.5	0.5	1	0.5	200	0.658297268	0.308358481
2582	0.05	10	0.5	0.5	3	0.5	200	0.662274845	0.318212979
2583	0.05	10	0.5	0.5	5	0.5	200	0.660833684	0.316596951
2584	0.05	10	0.5	0.5	7	0.5	200	0.662994414	0.322632965
2585	0.05	10	0.5	0.5	9	0.5	200	0.662539781	0.323281444
2586	0.05	10	0.5	0.5	11	0.5	200	0.662879701	0.325603642
2587	0.05	10	0.5	0.5	13	0.5	200	0.664546369	0.33050741
2588	0.05	10	0.5	0.5	15	0.5	200	0.666101424	0.334410689
2589	0.05	10	0.5	0.5	17	0.5	200	0.667844149	0.339042675
2590	0.05	10	0.5	0.5	19	0.5	200	0.666895802	0.338030192
2591	0.05	10	0.6	0.5	1	0.5	200	0.660719445	0.313254043
2592	0.05	10	0.6	0.5	3	0.5	200	0.66280605	0.318439727
2593	0.05	10	0.6	0.5	5	0.5	200	0.663410047	0.322144815
2594	0.05	10	0.6	0.5	7	0.5	200	0.66488814	0.326980179
2595	0.05	10	0.6	0.5	9	0.5	200	0.665077919	0.328362767
2596	0.05	10	0.6	0.5	11	0.5	200	0.664889344	0.329169531
2597	0.05	10	0.6	0.5	13	0.5	200	0.667122946	0.335310294
2598	0.05	10	0.6	0.5	15	0.5	200	0.664356932	0.330429223
2599	0.05	10	0.6	0.5	17	0.5	200	0.669243814	0.341384897
2600	0.05	10	0.6	0.5	19	0.5	200	0.665646921	0.335235197
2601	0.05	10	0.7	0.5	1	0.5	200	0.660079121	0.312880935
2602	0.05	10	0.7	0.5	3	0.5	200	0.661783065	0.31699176
2603	0.05	10	0.7	0.5	5	0.5	200	0.663259737	0.321905553
2604	0.05	10	0.7	0.5	7	0.5	200	0.666745107	0.33094341
2605	0.05	10	0.7	0.5	9	0.5	200	0.662197409	0.322628684
2606	0.05	10	0.7	0.5	11	0.5	200	0.66356393	0.327082832
2607	0.05	10	0.7	0.5	13	0.5	200	0.663448615	0.328143259
2608	0.05	10	0.7	0.5	15	0.5	200	0.667920811	0.33819999
2609	0.05	10	0.7	0.5	17	0.5	200	0.668107235	0.340096071
2610	0.05	10	0.7	0.5	19	0.5	200	0.671972813	0.348324482
2611	0.05	10	0.8	0.5	1	0.5	200	0.662310099	0.316921813
2612	0.05	10	0.8	0.5	3	0.5	200	0.662539565	0.318197139
2613	0.05	10	0.8	0.5	5	0.5	200	0.663715618	0.323225386
2614	0.05	10	0.8	0.5	7	0.5	200	0.660987395	0.318646003
2615	0.05	10	0.8	0.5	9	0.5	200	0.664622555	0.327691817
2616	0.05	10	0.8	0.5	11	0.5	200	0.664205674	0.328274976
2617	0.05	10	0.8	0.5	13	0.5	200	0.664699046	0.330549436
2618	0.05	10	0.8	0.5	15	0.5	200	0.66739038	0.337452864
2619	0.05	10	0.8	0.5	17	0.5	200	0.668598454	0.341006545
2620	0.05	10	0.8	0.5	19	0.5	200	0.669850306	0.344138186
2621	0.05	10	0.9	0.5	1	0.5	200	0.660116311	0.312741366
2622	0.05	10	0.9	0.5	3	0.5	200	0.661212559	0.316517873
2623	0.05	10	0.9	0.5	5	0.5	200	0.660909571	0.316614261
2624	0.05	10	0.9	0.5	7	0.5	200	0.662842597	0.322618743
2625	0.05	10	0.9	0.5	9	0.5	200	0.661479348	0.320865324
2626	0.05	10	0.9	0.5	11	0.5	200	0.664281088	0.32900536
2627	0.05	10	0.9	0.5	13	0.5	200	0.664737959	0.330935206
2628	0.05	10	0.9	0.5	15	0.5	200	0.668603231	0.339869393
2629	0.05	10	0.9	0.5	17	0.5	200	0.665986194	0.335518876
2630	0.05	10	0.9	0.5	19	0.5	200	0.66962355	0.343854377
2631	0.05	10	1	0.5	1	0.5	200	0.661860116	0.316773817
2632	0.05	10	1	0.5	3	0.5	200	0.661894767	0.318022839
2633	0.05	10	1	0.5	5	0.5	200	0.660268645	0.315710914
2634	0.05	10	1	0.5	7	0.5	200	0.661214237	0.31980148
2635	0.05	10	1	0.5	9	0.5	200	0.662009609	0.322929823
2636	0.05	10	1	0.5	11	0.5	200	0.665115196	0.33078147
2637	0.05	10	1	0.5	13	0.5	200	0.665722377	0.332469919
2638	0.05	10	1	0.5	15	0.5	200	0.664964585	0.332285139
2639	0.05	10	1	0.5	17	0.5	200	0.668107281	0.340097317
2640	0.05	10	1	0.5	19	0.5	200	0.668035654	0.340528604