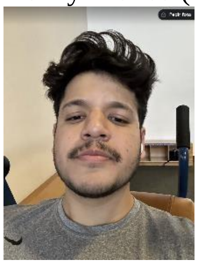
Project Step 0:

Team member: Data Miners Unearthed

Members:

- Kenny Aranda (n01513222)



- Zeke Geiger (n01360784)

- Ross Crawford (n01431391)

Project title: Airline Passenger Satisfaction Prediction.

Data: Airline passenger satisfaction dataset.

Airline passenger satisfaction (https://www.kaggle.com/datasets/teejmahal20/airline-passenger-satisfaction)

Leaders:

Step 1 leader: Zeke Geiger; Step 2 leader: Kenny Aranda; Step 3 leader: Ross Crawford; Step 4 leader: Zeke Geiger

Communication: We plan to have a group chat through Discord or Microsoft teams. We are going to communicate twice a week to review the assignments for the project steps.

Tools: Weka, Microsoft word, Teams

Project Step 1:

The problem involves analyzing an airline passenger satisfaction dataset to uncover factors that are highly correlated with passenger satisfaction or dissatisfaction. The primary task is to predict passenger satisfaction based on the features in Figure 1:

#	id	Gender	Customer ...	Age	Type of Tr...
0	19556	Female	Loyal Customer	52	Business travel
1	90035	Female	Loyal Customer	36	Business travel
2	12360	Male	disloyal Customer	20	Business travel
3	77959	Male	Loyal Customer	44	Business travel
4	36875	Female	Loyal Customer	49	Business travel
5	39177	Male	Loyal Customer	16	Business travel
6	79433	Female	Loyal Customer	77	Business travel
7	97286	Female	Loyal Customer	43	Business travel

Figure 1

Airlines can use insights from this analysis to identify areas where passenger satisfaction is low and make targeted improvements. This can lead to happier customers and increased loyalty. Additionally, understanding factors leading to dissatisfaction can help airlines allocate resources more efficiently to address the most critical issues, potentially reducing costs. Airlines that consistently provide high passenger satisfaction are likely to gain a competitive edge in the industry. Knowing what matters to passengers can help airlines differentiate their services.

Airlines are among the primary audience for this analysis. Airline companies can use this analysis to enhance their services, prioritize improvements, and tailor their offerings to meet passenger expectations. However, there are other audiences that can benefit. Passengers will benefit from improved airline services and overall satisfaction during their travels. Regulatory authorities can use the insight to monitor and enforce passenger satisfaction standards within the airline industry. Marketing teams can use the findings to develop targeted campaigns that highlight the strengths of their airline's services. Professionals in the field of data analysis and data science can gain insights into practical applications of data mining and predictive modeling using this real-world dataset.

While one might think humans could solve this problem, there is no feasible approach. Almost three million people fly in and out of U.S. airport every single day[1]. Additionally, the dataset we chose has over 100,000 datapoints, each with 22 factors that could affect customer satisfaction in varying and seemingly abstract ways. Assuming 1% of people flying in and out of the U.S. respond to a customer satisfaction survey, there are 30,000 new data entries every day that need to be analyzed. A computer-based solution is best; it can analyze the dataset using an algorithm and find the factors that most affect customer satisfaction. A solution to the problem would be able to analyze the data of a customer and their experiences/opinions of flight details and determine whether they were satisfied with the flight. It would take their data, such as their age and satisfaction with legroom, flight time, flight services, etc. and output if they were satisfied or neutral/dissatisfied with the flight. Figure 2 outlines the Black Box.

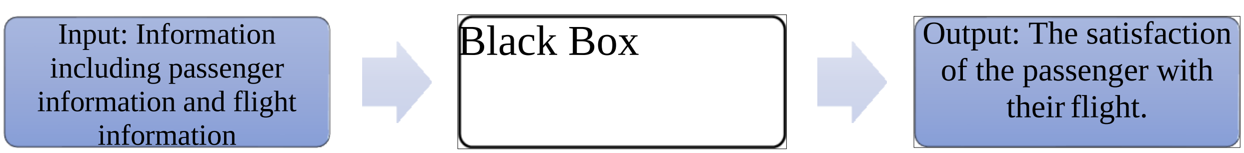


Figure 2

The dataset is sourced from Kaggle: https://www.kaggle.com/datasets/teejmahal20/airline-passenger-satisfaction. The data comes from TJ Klein, who compiled and reformatted information from an anonymous source.

test.csv	3.04mb	20% of full dataset
train.csv	12.19mb	80% of full dataset

[1] https://www.faa.gov/air_traffic/by_the_numbers

Project Step 2:

Attributes	Description	Nominal/Numeric
Gender	Gender of the passengers (Female, Male)	Nominal
Customer Type	The customer type (Loyal customer, disloyal customer)	Nominal
Age	The actual age of the passengers	Numeric
Type of Travel	Purpose of the flight of the passengers (Personal Travel, Business Travel)	Nominal
Class	Travel class in the plane of the passengers (Business, Eco, Eco Plus)	Nominal
Flight distance	The flight distance of this journey	Numeric
Inflight Wi-Fi service	Satisfaction level of the inflight Wi-Fi service	Numeric
Departure/Arrival time convenient	Satisfaction level of Departure/Arrival time convenient (1-5)	Numeric
Ease of Online booking	Satisfaction level of online booking (1-5)	Numeric
Gate location	Satisfaction level of Gate location (1-5)	Numeric
Food and drink	Satisfaction level of Food and drink (1-5)	Numeric
Online boarding	Satisfaction level of online boarding (1-5)	Numeric
Seat comfort	Satisfaction level of Seat comfort (1-5)	Numeric
Inflight entertainment	Satisfaction level of inflight entertainment (1-5)	Numeric
On-board service	Satisfaction level of On-board service (1-5)	Numeric
Leg room service	Satisfaction level of Leg room service (1-5)	Numeric
Baggage handling	Satisfaction level of baggage handling (1-5)	Numeric

Check-in service	Satisfaction level of Check-in service (1-5)	Numeric
Inflight service	Satisfaction level of inflight service (1-5)	Numeric
Cleanliness	Satisfaction level of Cleanliness (1-5)	Numeric
Departure Delay in Minutes	Minutes delayed when departure	Numeric
Arrival Delay in Minutes	Minutes delayed when Arrival	Numeric
Satisfaction	Airline satisfaction level (Satisfaction, neutral or dissatisfaction)	Nominal

We want to predict what attributes affect customer satisfaction to determine the most effective attributes to change. Therefore, satisfaction is the attribute picked as the class. Since a customer is either satisfied or neutral/dissatisfied, we are dealing with a binary classification problem. Below is a table listing all of the attributes, their descriptions, and their types:

Our data is split into two .csv files; a training file and a test file. They are split as such:

File name	# of Instances	# of Attributes
Train.csv	103904	24
Test.csv	25976	24

The numeric attributes of the training dataset and test dataset along with the minimum and maximum values, the mean, and the standard deviation are shown in a table below. The values from both datasets are the same in most cases and similar in the rest. For example, the departure delay and arrival delay attributes have a higher max value in the training dataset than the test dataset. Since the training dataset has 4 times the number of instances compared to the test dataset, it has more room for extreme values that can skew the statistics.

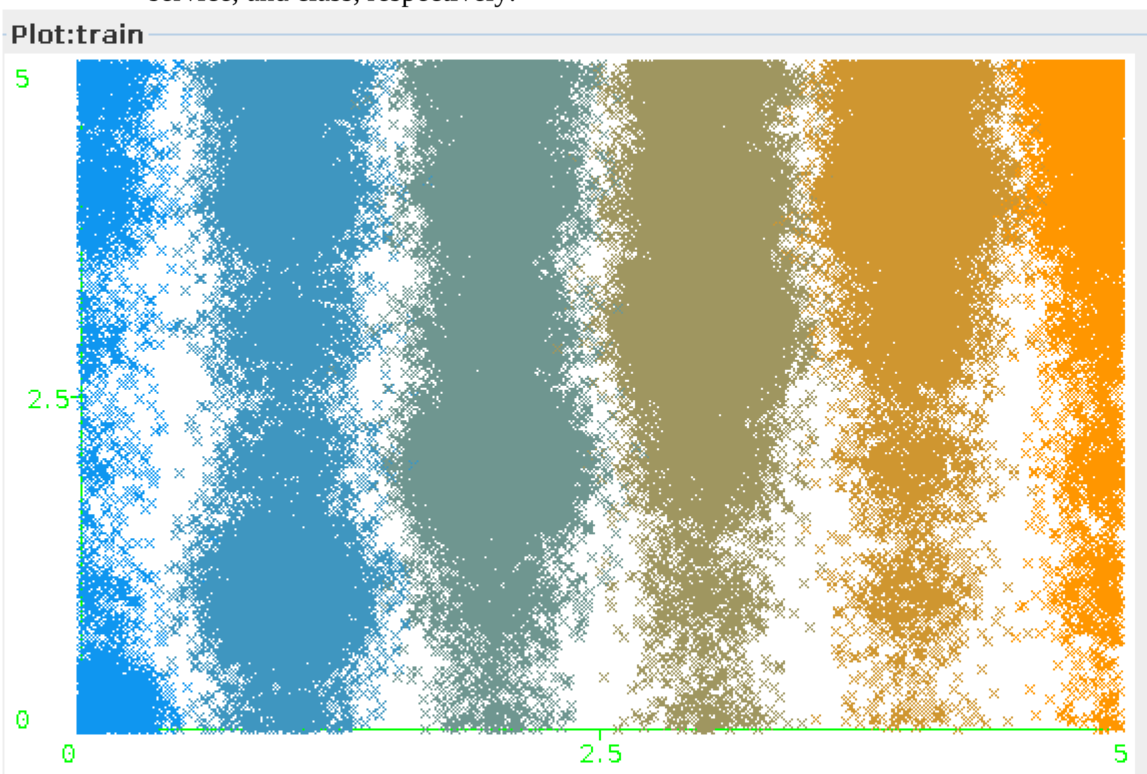
Attribute	Min (train | test)	Max (train | test)	Mean (train | test)	StDev (train | test)
Flight Distance	31 | 31	4983 | 4983	1189.4 | 1193.8	997.1 | 998.7
Inflight Wi-Fi Service	0 | 0	5 | 5	2.73 | 2.73	1.33 | 1.34
Departure/Arrival Time Convenience	0 | 0	5 | 5	3.06 | 3.05	1.53 | 1.53
Ease of Online Booking	0 | 0	5 | 5	2.76 | 2.76	1.40 | 1.41
Gate Location	0 | 0	5 | 5	2.98 | 2.98	1.28 | 1.28
Food and Drink	0 | 0	5 | 5	3.20 | 3.21	1.33 | 1.33
Online Boarding	0 | 0	5 | 5	3.25 | 3.26	1.35 | 1.36
Seat comfort	0 | 0	5 | 5	3.43 | 3.45	1.31 | 1.32
Inflight entertainment	0 | 0	5 | 5	3.36 | 3.36	1.33 | 1.34
On-board service	0 | 0	5 | 5	3.38 | 3.39	1.29 | 1.28
Leg room service	0 | 0	5 | 5	3.35 | 3.35	1.31 | 1.31
Baggage handling	0 | 0	5 | 5	3.63 | 3.63	1.18 | 1.17
Check-in service	0 | 0	5 | 5	3.30 | 3.31	1.27 | 1.27

Inflight service	0 | 0	5 | 5	3.64 | 3.65	1.18 | 1.18
Cleanliness	0 | 0	5 | 5	3.29 | 3.29	1.31 | 1.32
Departure Delay (in minutes)	0 | 0	1592 | 1128	14.82 | 14.31	38.23 | 37.42
Arrival Delay (in minutes)	0 | 0	1584 | 1115	15.18 | 14.74	38.70 | 37.52

The class distribution is also similar for both the training dataset and test dataset. While the amount is different for each dataset, they still retain the same proportion of satisfied-to-neutral/dissatisfied.

- **STEP 4: Explore the training data:**

  The three attributes most correlated with the class are online boarding, inflight wifi service, and class, respectively.



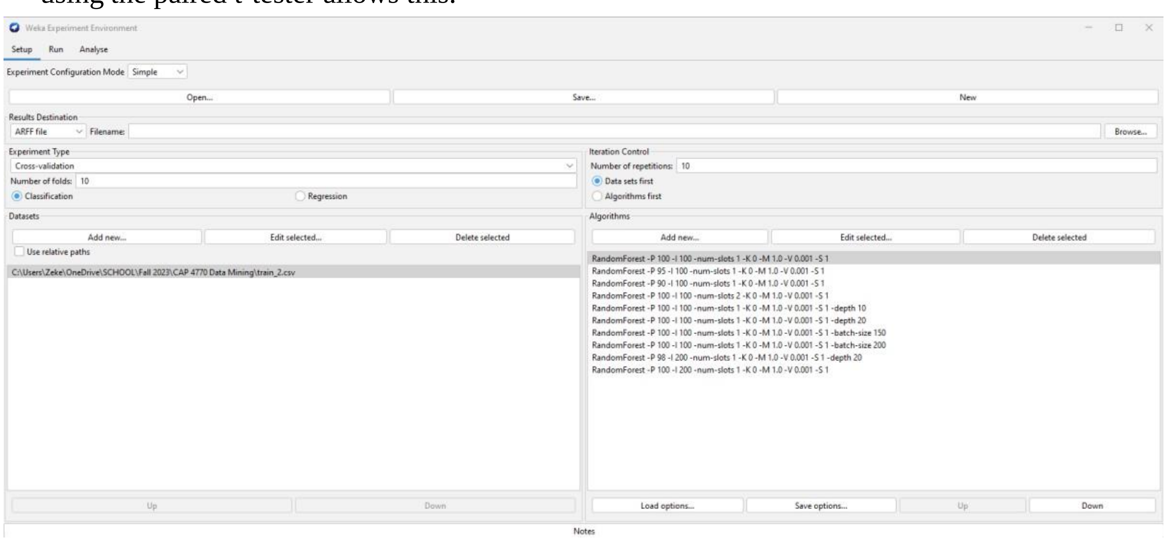
ZeroR	Naive Bayes	J48	KSTAR	LMT
56%	86%	72%	82%	73%

Naive Bayes performed suprisingly well with the base line correctly classifying just over half of the dataset

Project Step 3:

1a. The Random Forest classifier is an ensemble learning method that combines multiple Decision Trees to improve prediction accuracy. It works by building several Decision Trees on subsets of the data and then combining their predictions. This reduces overfitting and enhances accuracy, making it a popular choice for various machine learning tasks.
1b. Random Forest differs from other ensemble classifiers in that it builds multiple Decision Trees with feature selection randomness, reducing overfitting and enhancing accuracy. Other ensemble methods like bagging, boosting, voting, and stacking use different strategies and may combine diverse base models for different purposes.
2a.
RandomForest 1: No changed settings (Baseline)
RandomForest 2: bagSizePercent changed to 95
RandomForest 3: bagSizePercent changed to 90
RandomForest 4: numExecutionSlots changed to 2
RandomForest 5: maxDepth changed to 10
RandomForest 6: maxDepth changed to 20
RandomForest 7: batchSize changed to 150
RandomForest 8: batchSize changed to 200
RandomForest 9: bagSizePercent changed to 98, numIterations changed to 200, and depth to 20
RandomForest 10: numIterations changed to 200.

2b. To validate the RandomForest algorithms, we are using 10-fold cross validation. This separates the data into "folds" or sections, where nine folds are used to train the algorithms on the supplied dataset and the final fold is used as testing. This is then repeated nine more times; each fold will be a testing fold at least once. The results are then averaged at the end. We are using this validation technique because it allows us to test the algorithms on ten test sets for each algorithm. If we did a training/testing dataset split, we would only test the algorithm parameters once; doing cross-validation allows us to test it ten times.
2c. To test our performance, we used the corrected paired t-tester. The Paired T-tester lets us compare the mean of the baseline RandomForest algorithm cross validation with the means of the other RandomForest algorithm cross validations. Each run of the cross validation on an algorithm is paired with the run on the baseline. After this, we use an equation comparing the sample size, the sample mean of the differences, and the sample standard deviation of the differences. If the number given is higher or lower than the significance defined (in our case, we used 0.05,) then the algorithm is deemed to be statistically better or worse than the baseline algorithm. We used the corrected paired t-tester because we are using the same dataset; the algorithms can be paired one-to-one because they have the same sample size and the same objective. Additionally, we are trying to prove that changing the parameters on the algorithm can have a higher performance; using the paired t-tester allows this.



3A.

#	Percentage P	Iterations I	Num-slots	K	M	V	S	Depth	Batch-size	Percent_correct	Significance
1	100	100	1	0	1.0	0.001	1	-	-	96.42	-
2	95	100	1	0	1.0	0.001	1	-	-	96.42	-
3	90	100	1	0	1.0	0.001	1	-	-	96.40	*
4	100	100	2	0	1.0	0.001	1	-	-	96.42	-
5	100	100	1	0	1.0	0.001	1	10	-	94.86	*
6	100	100	1	0	1.0	0.001	1	20	-	96.38	*
7	100	100	1	0	1.0	0.001	1	-	150	96.42	-
8	100	100	1	0	1.0	0.001	1	-	200	96.42	-
9	98	200	1	0	1.0	0.001	1	20	-	96.41	-
10	100	200	1	0	1.0	0.001	1	-	-	96.45	v

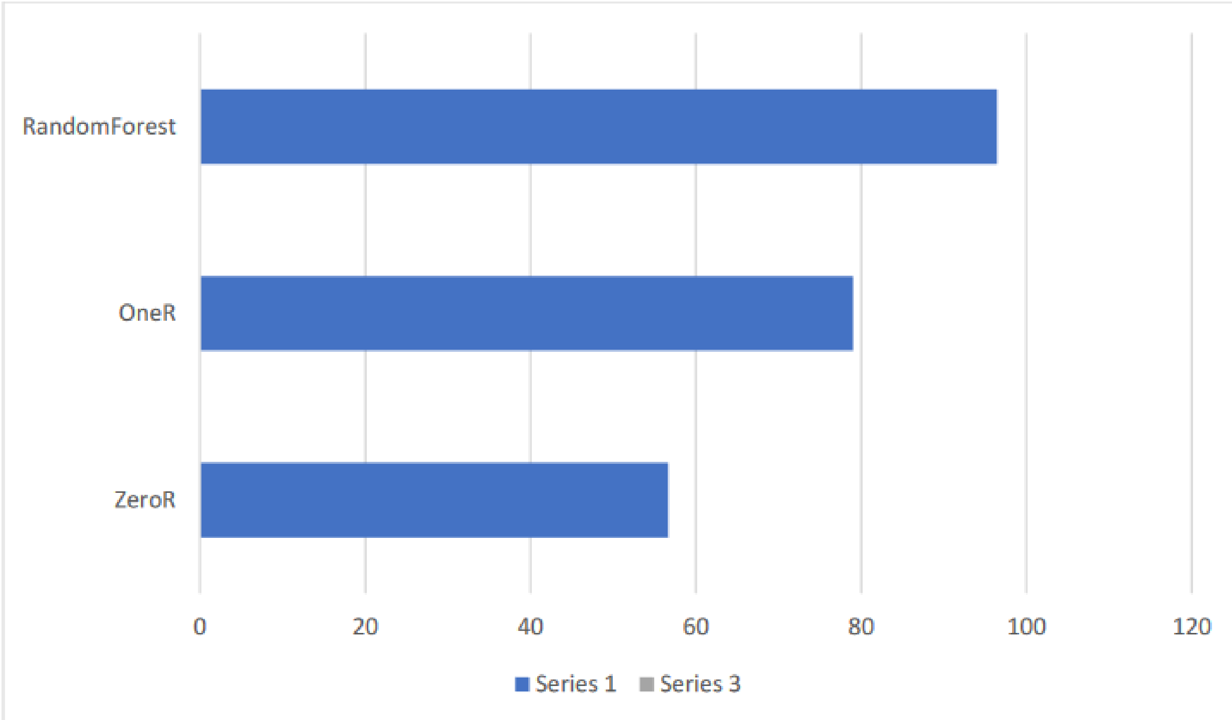
Significance Key:

- v: Significantly better
- *: Significantly worse
- -: Not significantly different

The 10th combination, with **P=100**, **I=200**, and **num-slots=1**, achieved the highest accuracy of 96.45% and is marked as significantly better (**v**) compared to the default parameters. The results show that increasing the number of iterations (**I**) from 100 to 200 (as in the 9th and 10th combinations) improves the performance, which is intuitive since more iterations allow the Random Forest to learn better.

4A.

ZeroR is the simplest classification method which relies on the target and ignores all predictors. OneR is slightly more complex than ZeroR. it generates one rule for each predictor in the data, and then selects the rule with the smallest total error as its "one rule".



Baseline Performances: ZeroR, being the simplest classifier that predicts the majority class,has the lowest performance at 56.67%. OneR, which considers one rule for prediction, performs significantly better than ZeroR with a performance of 79.04%.

RandomForest's Superiority: The RandomForest classifier, with the specified parameters, outperforms both baselines by a significant margin, achieving a performance of 96.45%. Thisshowcases the power of ensemble methods like RandomForest, which combine multiple decision trees to produce a more accurate and stable prediction.

Comparison with Baselines: It's crucial to compare sophisticated models with simple baselines like ZeroR and OneR. The vast difference in performance between RandomForest and the baselines emphasizes the effectiveness of the RandomForest model for this particulardataset.

Potential Overfitting: While the RandomForest's performance is impressive, it's close to 100%, which might indicate potential overfitting to the training data. It would be essential tovalidate the model's performance on a separate test set to ensure its generalization capabilities.

Project Step 4:

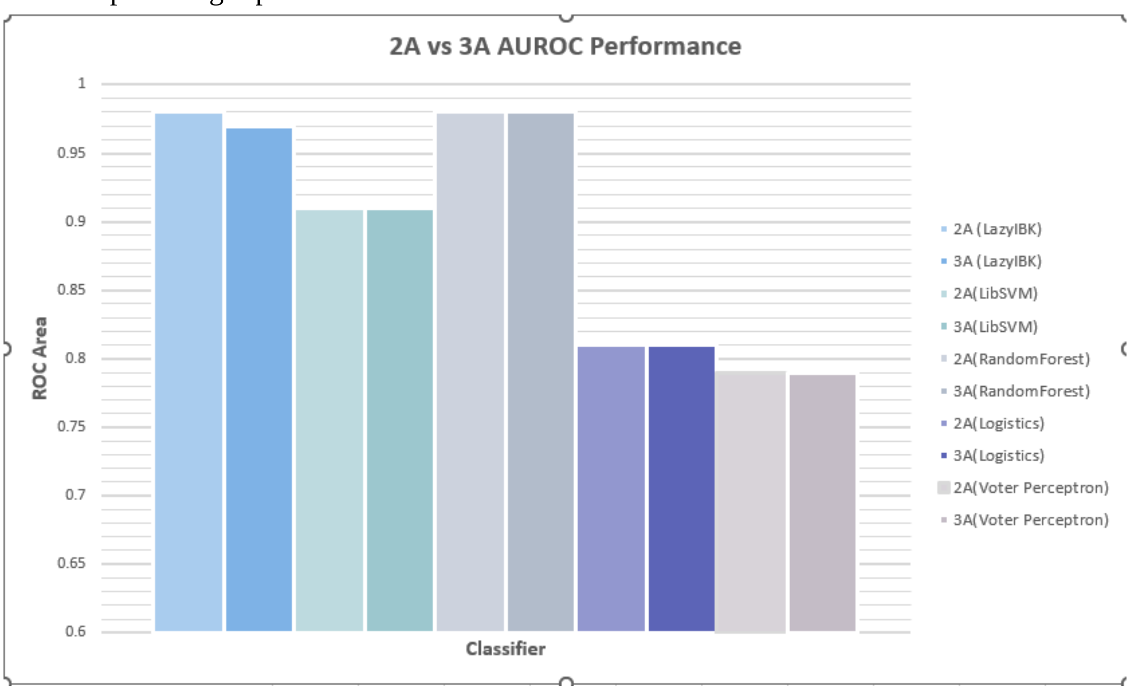
Using the CVSParamterSelection classifier inside of the AttributeSelectedClassifier, we tested hyperparameters (when applicable) on multiple classifiers similar to the tests we did on RandomForest in step 3. We tested five classifiers on our training dataset: LazyIBK(nearest neighbor), LibSVM(support vector machines), RandomForest, Logistics, and VoterPerceptron. We used 10 times 10-fold cross validation as our validation technique and looked at ROC area as our primary performance metric and precision and accuracy as our secondary metrics.

After gathering the results, we tested the classifiers on the "train+test" dataset, which is a combination of the training and test dataset. We used the same parameters and the same performance metrics but ran the classifiers using the "Train/Test Percentage Split" (80/20) technique instead of cross validation. A table comparing the results of the cross validation and train/test split is below on the left. A table showing the true positive, true negative, false positive, and false negative (TP, TN, FP, and FN, respectively) of the test data is below on the right:

2A vs 3A performance	AUROC	Precision	Accuracy
2A (LazyIBK)	0.98	0.92	92.4%
2A(LibSVM)	0.91	0.91	91.3%
2A(RandomForest)	0.98	0.93	92.3%
2A(Logistics)	0.81	0.85	78.8%
2A(Voter Perceptron)	0.79	0.79	79.9%
3A (LazyIBK)	0.97	0.92	92.3%
3A(LibSVM)	0.91	0.92	91.4%
3A(RandomForest)	0.98	0.93	92.3%
3A(Logistics)	0.81	0.85	78.3%
3A(Voter Perceptron)	0.79	0.79	79.8%

TP-TN/FP-FN Amount	TP	TN	FP	FN
3A (LazyIBK)	13734	10241	1162	839
3A(LibSVM)	13481	10248	1155	1092
3A(RandomForest)	13647	10329	1074	926
3A(Logistics)	10955	9395	2008	3618
3A(Voter Perceptron)	12717	8002	3401	1856

The bar plot below shows the ROC area (AUROC) results of the classifiers using cross validation and train/test percentage split:



1) A bar graph depicting the AUROC (area under ROC) performance for 10-times 10-fold cross validation (2A) versus 80/20 train/test percentage split (3A). The top performers were RandomForest, followed by LazyIBK and SVM

The table and bar plot both show that cross validation performs very similar to train/test percentage split. The primary and secondary metrics were very similar for LazyIBK and RandomForest, which shows that the hyperparameters changed have a significant effect on performance. They also have similar amounts for the positive and negative amounts, with LazyIBK trading a lower false-negative amount for a higher false-positive amount. Since Logistics and Voter Perceptron had no hyperparamter tuning, it makes sense that they performed worse. Additionally, Logistics used a different evaluator in the AttributeSelectedClassifier than the rest of the classifiers, which might affect performance. Since we tested RandomForest hyperparameters in step 3, it makes sense that it would perform the best; it had the most testing done.

We chose RandomForest as our top model due to the results from Experimenter. Running the classifier in Weka Explorer using the same parameters as previous testing selected the following as the top five attributes: type of travel, class, inflight Wi-Fi service, online boarding, and inflight entertainment. These attributes are intuitive. Business travel usually has expenses paid so it is usually higher quality/lower stakes. First class passengers would rate their flight experience higher than those in more cramped and less serviced seats. Airline passengers, especially those on business, would want to have high-quality and consistent Wi-Fi, which makes sense. Virtually all flights are booked online, so an easy booking process would leave a positive experience. Finally, in-flight entertainment helps keep passengers entertained and distracted from less desirable experiences during the flight. Comparing this to a RandomForest model to search for cancer (must have high standards), we see our model performs just slightly less at 92.24% compared to 94% of the cancer classification[1]. This means our model performs very well and these attributes have a high link to airline satisfaction.

In conclusion, the analysis identified key attributes strongly correlated with passenger satisfaction. These included the type of travel, class, inflight Wi-Fi service, online boarding, and inflight entertainment. Understanding the impact of these factors can help airlines prioritize improvements. Enhancing these aspects might lead to increased passenger satisfaction and loyalty. The type of travel and class might impact satisfaction differently for various passenger segments. For instance, business travelers might prioritize different amenities compared to leisure travelers within the same class. Inflight Wi-Fi service and online boarding emerged as influential factors. Investing in better connectivity and streamlined boarding processes could significantly enhance passenger experiences. Highlighting these strengths in marketing and service offerings might attract more passengers. Insights gleaned from this analysis can guide future decision-making processes for airlines. It provides a roadmap for focusing resources and efforts on areas that matter most to passengers.

One potential limitation of our work was the exclusive use of some classifiers instead of exploring other machine learning algorithms, such as TensorFlow classifiers. TensorFlow allows for building complex neural network models that might capture intricate patterns within the data, potentially leading to more nuanced insights. Time and resource constraints limited our ability to explore a wider array of models (such as SMO) that could potentially yield different insights or more accurate predictions. Additional hyperparameters and hyperparameters with a wider range of values couldn't be tested for a similar reason.

[1] https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6858312/

Appendix:

Hyperparameters:

IBK: K 1.0 3.0 2.0

LibSVM: G 0.01 0.05 2.0

RandomForest: Had hyperparameter tuning available, but chose the best result from Step 3

Teamwork Evaluation:

Member 1: Kenny Aranda

Member 2: Zeke Geiger

Member 3: Ross Crawford

Step	Member 1	Member 2	Member 3
Step 1	**33.33%**	**33.33%**	**33.33%**
Step 2	**33.33%**	**33.33%**	**33.33%**
Step 3	**33.33%**	**33.33%**	**33.33%**
Step 4	**33.33%**	**33.33%**	**33.33%**