CONSULTING METHODS APPLIED TO AI PROJECTS

PREDICTING AMERICAN AIRLINES FLIGHT DELAYS WITH AI: IMPROVING CUSTOMER SATISFACTION AND FLIGHT OPERATIONS

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AI REPORT

I. Introduction

1. Executive Summary

The purpose of this report is to demonstrate the potential benefits of using Artificial Intelligence (AI) to predict and mitigate flight delays and cancellations for American Airlines customers. The airline industry faces several challenges in managing flight schedules, and AI has the potential to provide valuable insights and solutions to improve decision-making and customer experience. This project uses historical data and real-time information on weather conditions and operational issues to develop an AI-based solution that can provide airlines with valuable insights to reduce negative impacts on customers.
This report provides an overview of the development and implementation of the AI solution, including the methodology used for data collection, algorithm selection, training, and testing of the AI model. The report presents the results and findings of the AI solution, including performance metrics and comparison with traditional methods of prediction. Finally, the report concludes with recommendations for implementation and future work. While this report does not provide a detailed technical explanation of the AI algorithms used in the solution, it focuses on the practical applications and benefits of using AI for predicting and mitigating flight delays and cancellations.

2. Background and context of the problem

Description of the issue with flight delays and cancellations

The airline industry is facing increasing challenges in managing flight schedules and reducing delays. Weather conditions and operational issues can significantly impact an airline's reputation and cause inconvenience and frustration for customers. With the rise of digital technologies, the use of Artificial Intelligence (AI) in the aviation industry has become increasingly popular. AI has the potential to provide valuable insights and solutions to mitigate flight disruptions and improve customer experience.

Flight delays continue to be a significant issue in the United States, with substantial economic consequences. According to a 2018 report from the Federal Aviation Administration (FAA), the annual cost of flight delays and cancellations in the country is estimated to be around $28 billion. This figure encompasses direct costs to airlines and passengers, as well as indirect costs such as lost productivity and adverse effects on the economy. However, it is crucial to note that these figures may fluctuate from year to year due to a variety of factors, including weather conditions, airline operations, and the performance of the air traffic control system.

By addressing the issue of flight delays, airlines have the potential to save a significant amount of money, not only in direct operational expenses but also by improving customer satisfaction and maintaining a positive brand reputation. Reducing flight delays can lead to lower fuel consumption, decreased staff overtime payments, and diminished compensation costs for affected passengers. Furthermore, by enhancing the overall travel experience, airlines can boost customer loyalty, leading to higher retention rates and increased revenue from repeat business. In addition, mitigating flight delays can result in better resource allocation, allowing airlines to optimize their operations, which could ultimately generate substantial cost savings. Consequently, investing in AI-based solutions and other innovative technologies to minimize flight delays is a worthwhile endeavor for airlines, as it has the potential to yield significant financial benefits in the long run.

3. Purpose of the report

Using AI to solve the problem

The goal of this project is to develop an AI-based solution that can predict and mitigate flight delays and cancellations for American Airlines customers. By using historical data and real-time information on weather conditions and operational issues, the AI solution will provide airlines with valuable insights to improve decision-making and reduce negative impacts on customers. This project aims to demonstrate the benefits of using AI in the airline industry and provide recommendations for its implementation and future work.

4. Scope of the report

The scope of this report is to provide an overview of the development and implementation of an AI solution for predicting and mitigating flight delays and cancellations for American Airlines customers. The report will cover the following in-scope topics:

1. In-scope:

- Problem statement and background information on the challenges faced by the airline industry.
- Methodology used for data collection, algorithm selection, training and testing of the AI model.
- Results and findings of the AI solution, including performance metrics and comparison with traditional methods of prediction.
- Conclusion and recommendations for implementation and future work.

2. Out-of-Scope:

- Analysis of data privacy and security concerns related to the use of AI in the aviation industry.
- Discussion of broader ethical and societal implications of using AI in the airline industry.

This report will provide an overview of the AI solution and its results but is not intended to be an exhaustive technical manual. The report will focus on the practical applications and benefits of using AI for predicting and mitigating flight delays and cancellations.

II. Problem Statement

1. Description of the issue and flight delays and cancellations for American Airlines

Flight delays and cancellations are a pervasive issue within the aviation industry, affecting millions of passengers worldwide. Unfortunately, American Airlines is no exception to this issue. Like other airlines, American Airlines faces several causes of flight delays, including weather conditions, mechanical issues, staffing problems, and air traffic control.

Weather conditions are one of the most common causes of flight delays, particularly during extreme weather events such as snowstorms, hurricanes, or thunderstorms (U.S. Department of Transportation, n.d.). These events can result in flight cancellations or delays as airlines prioritize the safety of passengers and crew.

Mechanical issues are another leading cause of flight delays. These can range from minor malfunctions such as broken air conditioning or in-flight entertainment systems to more serious issues such as engine failures or landing gear problems (U.S. Department of Transportation, n.d.). In such cases, the airline must ground the affected aircraft for repairs, which can result in significant delays or cancellations.

Staffing problems can also lead to flight delays or cancellations, particularly if there are not enough flight crew members available or if the crew members exceed their working hours limit (Wagner, 2022). These issues can occur due to unexpected absences or high demand for flight crews.

Air traffic control issues can also cause flight delays. Congestion in the airspace, runway closures, or changes in flight patterns can all cause delays in take-off or landing times (U.S. Department of Transportation, n.d.).

2. The impact of the problem on American Airlines customers

Flight delays are a common occurrence for airline passengers and can have a significant impact on their experience and overall satisfaction with an airline. For American Airlines customers, flight delays can result in a range of negative consequences, from increased frustration and stress to financial losses and reduced reputation.

The Convenience Factor

The inconvenience factor of flight delays is perhaps the most widely felt by customers. Delays can cause stress, frustration, and a sense of wasted time for passengers who may have important appointments or travel plans disrupted by the delay (Wong, 2011). This is especially true for business travellers who are on tight schedules and need to attend important meetings, as flight delays can cause them to miss these crucial opportunities.

The Financial Impact

In addition to the inconvenience factor, flight delays can also result in significant financial losses for customers. For example, if a customer misses a connecting flight due to a delay, they may need to book additional accommodation, transportation, and meals, which can quickly add up and result in unexpected expenses. This can be especially damaging for business travelers who are on tight schedules and need to attend important meetings (Peterson, 2013).

Reduced Reputation

Flight delays can also have a negative impact on the reputation of an airline. Consistently delayed flights can lead to a decline in customer loyalty and a decrease in the airline's brand image and reputation. This can have long-term consequences, as customers may choose to fly with a different airline in the future if they feel that their experience with American Airlines was unsatisfactory (Team, 2016).

Impact on Businesses

Finally, flight delays can also have a financial impact on businesses. Employees who are traveling for work may be unable to attend important meetings or complete important tasks if their flight is delayed. This can result in reduced productivity, missed opportunities, and increased costs for the business (Peterson, 2013).

Reducing the Impact of Flight Delays

In conclusion, the impact of flight delays on American Airlines customers can be significant and far-reaching. To mitigate these impacts, airlines need to prioritize reducing delays and improving the overall customer experience (Wong, 2011). By taking steps to reduce flight delays and improve the customer experience, American Airlines can help to maintain customer satisfaction and loyalty, while also mitigating the negative consequences of flight delays for its customers.

Some statistical data to provide further context:

- In 2019, American Airlines had the 9th highest number of delayed flights of any U.S. airline, with an average delay time of 0.34 minutes (U.S. Department of Transportation, n.d.).
- In a report by FAA it was found that flight delays in the United States result in an estimated $18.1 billion in lost passenger time and increased operating costs for airlines (*Cost of delay estimates, 2019.)*.

These statistics provide further evidence of the impact of flight delays on American Airlines customers and the airline industry as a whole.

One of the Current solutions for customers: Search for alternatives using technology.
If there is a severe enough delay that the flight needs to be changed, American will rebook the passenger on the next flight with available seats and reroute the luggage as the passenger checks in for a new flight.

Bothering airline employees will not help the situation. Instead, stay calm, and if the flight is delayed for too long, use the Airlines app, website or an airline kiosk to see if there is an earlier flight available that one can switch to.
The app allows the passenger to view flight schedule changes, and the website will show them, and one can accept airline-proposed itineraries. Both tools allows the passenger to schedule a new flight if necessary. (McDarris, n.d.)

3. Objectives and goals of the AI solution

The objectives and goals of AI solutions for flight delays and cancellations are as follows:

1. Improve operational efficiency: AI solutions can be utilized to optimize flight schedules, reduce wait times for maintenance, and better allocate staff resources to reduce delays caused by staffing problems.

2. Enhance safety: AI solutions can provide real-time weather updates and enable airlines to make informed decisions about flight cancellations or delays to prioritize the safety of passengers and crew.

3. Predict and prevent mechanical issues: AI-powered predictive maintenance can monitor the condition of aircraft components and predict when repairs are needed, reducing the likelihood of mechanical issues causing delays.

4. Optimize air traffic control: AI solutions can be used to optimize air traffic control by analysing flight data and identifying congestion points to prevent delays caused by air traffic control issues.

5. Provide better communication and transparency: AI solutions can be utilized to provide real-time updates to passengers on flight delays and cancellations, ensuring that they are informed and can make alternative travel arrangements as necessary.

6. Improve the customer experience: By reducing flight delays and providing better communication, AI solutions can improve the overall customer experience and increase customer satisfaction with the airline.

These are all the possible AI solutions for the problems defined above. We are more focused on the 5th and 6th points, and we have considered doing the following:

- Get a heads up on potential log jams, check out FlightAware's interactive Misery Map to see which airports are shaping up to be migraine hubs. Hover over a problematic airport, and the map will show you which routes are experiencing the most delays and cancellations.
- Provide or enable better access to more accurate information for current customers.
- Increase information accuracy to customers.
- Transform into a high-performing organization that excels at customer service.

III. Methodology

1. Data collection and preparation

Data collected https://www.transtats.bts.gov/OT_Delay/OT_DelayCause1.asp?20=E

Selected data from oct 2012to oct 2022 for American airline number of flight delay by month for each airport in the US during the time period.

Preparation:

The initial dataset had 21 variables when the data were downloaded from the website. However, the dataset was reduced to 13 variables for future study by a thorough data cleaning process. The following variables are part of the cleaned dataset:

- Name of the airport where the data was gathered, together with the city and state details, is given as the airport name.
- The data's applicable year and month are indicated by these two words.
- Arrival Flight: Details about the number of flight's arrival,
- Flight Delays: Information about flight delays that shows how many flights were delayed
- Causes of the delay: Flight delay causes are categorized, including carrier-related problems, weather-related problems, NAS (National Airspace System) problems, security-related problems, and problems with later aircraft.
- Time Delay in Hours: The length of a flight delay, translated from minutes to hours for easier understanding.

It is crucial to remember that the data is arranged on a monthly basis, and as a result, even after the data cleaning procedure, individual flight-level details are not available. However, the enhanced dataset with 13 variables offers an expert basis for additional analysis and insights into the determinants affecting flight delays at the selected airports.

Target: arr_delay

Features:

The features listed in the excel sheet are various variables that can be used to analyze flight data. Here is a brief explanation of each feature:

1. "Year" - This is the year for which the flight data is collected.
2. "Month" - This is the month for which the flight data is collected.
3. "Airport" - This is a code that identifies the airport where the flight arrived.
4. “city_state”- This is th name of the city and state where the flight arrived
5. "Airport_name" - This is the name of the airport where the flight arrived.
6. "Arr_flights" - This is the total number of flights that arrived at the airport during the specified time period.

7. "Arr_del15" - This is the number of flights that arrived 15 or more minutes later than their scheduled arrival time.
8. "Arr_delay" - This is the average delay time (in minutes) for flights that arrived at the airport during the specified time period.
9. "Carrier_delay" - This is the average delay time (in minutes) for flights that were delayed due to issues with the airline operating the flight.
10. "Weather_delay" - This is the average delay time (in minutes) for flights that were delayed due to weather conditions.
11. "Nas_delay" - This is the average delay time (in minutes) for flights that were delayed due to issues with the National Airspace System.
12. "Security_delay" - This is the average delay time (in minutes) for flights that were delayed due to security incidents.
13. "Late_aircraft_delay" - This is the average delay time (in minutes) for flights that were delayed due to arriving aircraft being late.

This data provides a snapshot of the performance of American Airlines flights arriving at John F. Kennedy International Airport in New York during the month of October 2012. Here are some insights that can be derived from the data:

1. Flight Arrivals: In October 2012, there were a total of 1086 flights that arrived at JFK airport operated by American Airlines.
2. Delays: 237 flights (22%) arrived 15 or more minutes later than their scheduled arrival time. This indicates that a significant number of flights were delayed during the month.
3. Carrier Delays: The average delay time for flights that were delayed due to issues with the airline operating the flight was 6529 minutes (109 hours). This represents the largest portion of the total delay time.
4. Weather Delays: The average delay time for flights that were delayed due to weather conditions was 76 minutes. This represents a relatively small portion of the total delay time.
5. National Airspace System Delays: The average delay time for flights that were delayed due to issues with the National Airspace System was 2149 minutes (35 hours).
6. Security Delays: There were no flights that were delayed due to security incidents.
7. Late Aircraft Delays: The average delay time for flights that were delayed due to arriving aircraft being late was 5321 minutes (88 hours).
8. Cancelled and Diverted Flights: There were 119 flights that were cancelled and 3 flights that were diverted to a different airport.

These insights provide a basic understanding of the flight operations of American Airlines at JFK airport in October 2012.

2. Choice of algorithm

The Orange ML program was utilized to choose the best machine learning algorithm. The following steps constitute the training portion of the process:

1. Import Excel File: The dataset was first imported into the Orange ML program in Excel format, which served as the main data source for the analysis.
2. The goal variable, "delay arrival," which stands for flight delays, was chosen as the variable of interest for the investigation. The machine learning model's target variable was chosen to be this variable.
3. Link Data Table: The software's data table and the imported dataset were connected, enabling additional data manipulation and analysis.
4. Selection of the Data for Training: 80% of the data was chosen for training the machine learning model. It is standard practice in machine learning to divide the data into training and testing sets in order to assess the performance of the model.
5. Create New Data Table: In the software, a new data table was made that solely contained the training data that had been chosen.
6. Choose Common Algorithms: To find the best machine learning method for the analysis, a number of algorithms were investigated, including gradient boosting, support vector machine (SVM), random forest, and linear regression. These algorithms were chosen based on their widespread application and success in comparable analyses.
7. Test & Score: Evaluate the performance of the different algorithms

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Description of each algorithm:

Linear regression is a statistical technique used to model the relationship between one or more independent variables and a dependent variable. It is frequently used to predict numerical values because it assumes a linear relationship between the variables.

Random forest: A machine learning algorithm that constructs multiple decision trees and combines their predictions to improve accuracy and reduce overfitting. It is frequently used for classification and regression problems.

SVMs are a type of machine learning algorithm that is used for classification and regression analysis. They determine the best boundary or hyperplane for differentiating classes or predicting the values of a target variable.

Gradient boosting is a machine learning technique that sequentially builds an ensemble of decision trees, with each subsequent tree trained to correct the errors of the previous ones. It is frequently used for regression and classification problems, and it can handle numeric and categorical data.

Gradient Boosting Algorithm detailed

Step 1: Initialize the model

We start by initializing the model with a constant value, such as the mean of the target variable y:

$$F_0(x) = mean(y)$$

This step sets the baseline prediction for the model, which is simply the mean value of the target variable. This is a simple starting point that can be improved upon with each iteration.

Step 2: Iterate over a fixed number of rounds

For each round $m=1,...,M$, we train a weak learner $h_m(x)$ that is trained to predict the residual errors from the previous round. We update the model by adding the weak learner to the previous model with a learning rate or shrinkage parameter λ:

$$F_m(x) = F_{m-1}(x) + \lambda h_m(x)$$

where λ is a small positive value that controls the step size of the gradient descent algorithm. This step is the heart of the algorithm, as it involves iteratively updating the model with a sequence of weak learners that are trained to correct the errors from the previous round.

Step 3: Training the weak learners

In order to train the weak learners, we need to calculate the residual errors from the previous round:

$$r_{m-1,i} = y_i - F_{m-1}(x_i)$$

where y_i is the target variable and x_i is the vector of input features for the i-th sample in the training set. We then train the weak learner $h_m(x)$ to predict these residual errors, using a loss function L:

$$h_m(x) = argmin_h L(y, F_{m-1}(x) + h(x))$$

The most commonly used loss function in gradient boosting is the mean squared error (MSE) for regression problems and the cross-entropy loss for binary classification problems. This step involves training a weak learner (often a decision tree) on the residual errors from the previous round, and using the loss function to optimize its performance.

Step 4: Final prediction

The final prediction is the sum of all weak learners, weighted by the learning rate:

F(x) = sum_{m=1}^M λ h_m(x)

This is the final model that is used to make predictions on new data. The learning rate controls the contribution of each weak learner to the final prediction and helps to prevent overfitting by slowing down the rate of learning.

Overall, the gradient boosting algorithm is a powerful technique for building complex models that can accurately predict the target variable in many different applications. The iterative nature of the algorithm allows it to gradually improve the performance of the model with each round, while the use of weak learners helps to prevent overfitting and improve generalization.

Quickest rate of change and Gradient Vector: We are going to utilize a gradient boosting algorithm.

The gradient vector is defined as a vector that points in the direction of the steepest increase of a function. The magnitude of the gradient vector represents the rate of change of the function in that direction. Mathematically, for a function f(x,y), the gradient vector is denoted by ∇f(x,y) and can be calculated using partial derivatives:

$$\nabla f(x,y) = (\partial f/\partial x , \partial f/\partial y)$$

Here, ∂f/∂x represents the partial derivative of f with respect to x, and ∂f/∂y represents the partial derivative of f with respect to y. The gradient vector ∇f(x,y) points in the direction of the steepest increase of the function at a given point (x,y) and its magnitude represents the rate of change of the function in that direction.

For example, if we have a function f(x,y) = x^2 + 2y, the gradient vector at a point (x,y) can be calculated as:

$$\nabla f(x,y) = (2x, 2)$$

This means that the function f(x,y) increases most rapidly in the direction of vector (2x,2), and the rate of increase is proportional to the magnitude of this vector. (Dawkins)

Now to understand the quickest rate of change it can be said that - The quickest rate of change of a data can be determined by finding the magnitude of the gradient vector at the point of interest. The magnitude of the gradient vector represents the rate of change in the direction of steepest ascent, which is the direction in which the function is increasing most rapidly.

So, at any given point in the function, the quickest rate of change can be found by computing the magnitude of the gradient vector at that point. The larger the magnitude of the gradient vector, the steeper the function is in that direction and the quicker the rate of change. Conversely, the smaller the magnitude of the gradient vector, the flatter the function is in that direction and the slower the rate of change.

It is worth noting that the rate of change can differ depending on the point of interest. In other words, the quickest rate of change may occur at one point in the function but not necessarily at another.

3. Training and testing of the AI model

Training and testing method:

Data Preprocessing:

The first step in any machine learning task is data preprocessing. This involves cleaning, transforming, and preparing the data for use in the model. For this task, we would need to gather data on flight delays and cancellations for American Airlines for a specific time period. Once we have the data, we would need to preprocess it by handling missing values, encoding categorical variables, and scaling numeric variables.

Splitting the Data:

After preprocessing the data, we would need to split it into training and testing datasets. The training dataset would be used to train the gradient boosting model, while the testing dataset would be used to evaluate its performance.

Training the Model:

Once we have split the data, we can begin training the gradient boosting model. This involves setting up the model with hyperparameters such as the number of trees, learning rate, and maximum depth of each tree. We then fit the model to the training dataset, allowing it to learn patterns and relationships in the data.

Testing the Model:

After training the model, we need to test its performance on the testing dataset. We do this by using the trained model to make predictions on the testing data and comparing these predictions to the actual values of flight delays and cancellations. We can use evaluation metrics such as mean squared error, root mean squared error, and accuracy to measure the performance of the model.

Tuning the Model:

Based on the results of testing the model, we may need to adjust the hyperparameters or try different approaches to improve its performance. This step involves fine-tuning the model and testing it again until we are satisfied with its performance.

Deploying the Model:

Once we have trained and tested the model, we can deploy it to make predictions on new data. This involves setting up an API or web interface that allows users to input data and receive predictions from the model.

Training Result with Test & Score in Orange :

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MSE (Mean Squared Error): MSE is a measure of the average squared difference between the predicted values and the actual values. It is calculated by taking the average of the squared differences between the predicted and actual values.

RMSE (Root Mean Squared Error): RMSE is the square root of the MSE. It gives us an idea of how far off the predictions are from the actual values.

MAE (Mean Absolute Error): MAE is a measure of the average absolute difference between the predicted values and the actual values. It is calculated by taking the average of the absolute differences between the predicted and actual values.

R2 (R-Squared): R2 is a measure of how well the regression line fits the data. It is calculated by dividing the variance of the predicted values by the variance of the actual values. R2 ranges from 0 to 1, with 1 indicating a perfect fit.

Test and Score

Model	MSE	RMSE	MAE	R2
Linear Regression	0.000	0.000	0.000	1.000
Gradient Boosting	1839450.221	1356.263	434.517	0.996
Random Forest	3345759.672	1829.142	410.428	0.993
Neural Network	12560571.737	3544.090	2212.971	0.974
SVM	2258308975.762	47521.668	45669.222	-3.640

The Linear Regression model has a perfect score for all evaluation metrics, including an MSE, RMSE, and MAE of zero, as well as an R2 score of 1.0, indicating that it can perfectly explain all the variance in the data.

The Gradient Boosting model has the lowest MSE and RMSE values, indicating that it makes better predictions than the other models. The MAE value is also low, indicating that the model's predictions are reasonably close to the actual values. The R2 score of 0.996 also indicates that the model explains a large portion of the variance in the data.

While a perfect score on all evaluation metrics may appear impressive, it is actually a warning sign that the model is overfitting the data. Overfitting occurs when a model is overly complex and overly closely fits the training data, resulting in poor performance on new, unseen data. The Linear Regression model, for example, may be overly simplistic and fail to capture the complexity of the data, resulting in overfitting.

Gradient Boosting, on the other hand, is a powerful algorithm that can handle complex relationships between features and target variables while avoiding overfitting. It combines several weak models to produce a robust, accurate model. In the case of flight delay prediction, Gradient Boosting's ability to handle complex feature relationships comes in handy.

Gradient boosting is a powerful machine learning algorithm that is widely used for supervised learning problems, such as classification and regression. It involves creating a strong predictive model by combining several weak models in a sequential manner.

The basic idea of gradient boosting is to iteratively add simple models to the ensemble in such a way that each new model focuses on improving the predictions of the previous models.

Testing:

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The methods used to test a gradient boosting model and evaluate the outcomes:

1. The data file was imported into a data table:
2. Created testing data choosing 20% of the data as the testing dataset.
3. Created a new data table with only testing data
4. Used the trained model and linked it to the testing data
5. Make predictions allowing to gauge the model performance on the testing data

Shown regression error: Absolute difference

Restore Original Order

	Gradient Boosting (1)	error	arr_del15	airport	city_state	airport_name	year	month	arr_flights	arr_delay	carrier_delay	weather_delay	n
1	265	28	237	JFK	New York, NY	John F. Kenn...	2012	10	1086	234.583	108.817	1.26667	35.8
2	825	51	876	LAX	Los Angeles,...	Los Angeles ...	2012	10	2520	710.05	232.8	8.55	207.
3	2667	78	2745	DFW	Dallas/Fort ...	Dallas/Fort ...	2012	10	12701	2311.72	769.05	39.0333	390.
4	49	7	42	OGG	Kahului, HI	Kahului Airport	2012	10	93	39.3167	13.55	0	11.9
5	80	4	84	HNL	Honolulu, HI	Daniel K Inou...	2012	10	186	65.65	34.8333	0	21.2
6	469	23	492	SFO	San Francisc...	San Francisc...	2012	10	910	448.883	112.75	4.68333	230.
7	229	23	252	BOS	Boston, MA	Logan Intern...	2012	10	878	210.717	95.65	5.75	47.3
8	942	74	1016	MIA	Miami, FL	Miami Intern...	2012	10	3582	865.55	318.367	11.7667	184.
9	63	9	54	IAD	Washington, ...	Washington ...	2012	10	244	55.3167	31.9	0	6.11
10	103	10	93	EWR	Newark, NJ	Newark Liber...	2012	10	292	76.35	19.9167	0.983333	45.7
11	148	28	176	SAN	San Diego, CA	San Diego In...	2012	10	394	130.133	53.6333	9.95	34.5
12	307	20	327	LGA	New York, NY	LaGuardia	2012	10	1366	281.783	83.3167	7.41667	118.1
13	1203	32	1235	ORD	Chicago, IL	Chicago O'H...	2012	10	4187	1139.47	291.683	9.36667	402.
14	139	5	144	DEN	Denver, CO	Denver Inter...	2012	10	391	111.967	56.1167	1.53333	24.2
15	175	46	221	AUS	Austin, TX	Austin - Ber...	2012	10	687	157.083	67.8333	2.1	30.3
16	281	41	322	LAS	Las Vegas, NV	McCarran Int...	2012	10	818	239.417	84.8833	2.68333	82.6
17	24	4	20	LIH	Lihue, HI	Lihue Airport	2012	10	47	15.35	5.06667	0	5.9
18	159	36	195	SEA	Seattle, WA	Seattle/Taco...	2012	10	447	131.317	55.05	2.6	42.7
19	46	10	56	SLC	Salt Lake Cit...	Salt Lake Cit...	2012	10	124	32.7	17.3333	0	12.2
20	78	13	91	IAH	Houston, TX	George Bush...	2012	10	333	61.7167	30.0333	0.2	9.63
21	70	20	90	MSP	Minneapolis,...	Minneapolis-...	2012	10	321	58.5167	22.9167	1.16667	10.7
22	165	20	185	STL	St. Louis, MO	St Louis Lam...	2012	10	743	145.583	63.3833	3.91667	21.7

Show perfomance scores

Model	MSE	RMSE	MAE	R2
Gradient Boosting (1)	354.037	18.816	9.349	0.996

The "Gradient Boosting" column presents the time delay predicted by the algorithm, along with the error, which is the time difference in hours compared to the actual data provided in the table. For instance, in October 2012, the algorithm predicted 265 hours of delays, while only 237 hours of delays were encountered, resulting in an error of 28 hours.

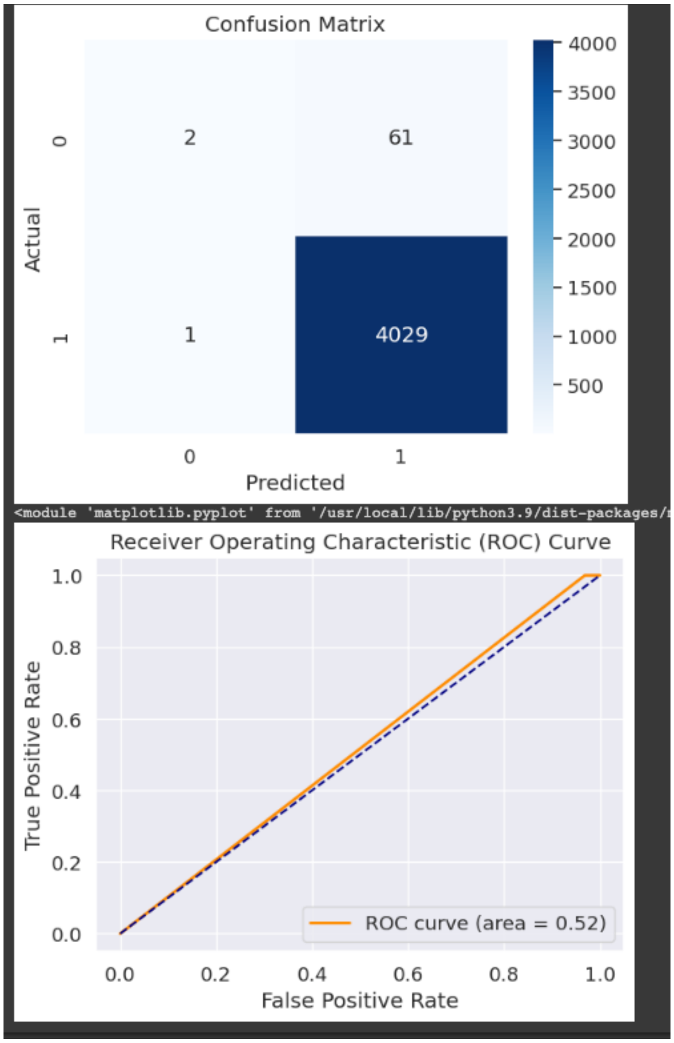
IV. Results and Findings

1. Performance metrics of the AI model

We developed a Python algorithm to obtain performance metrics for evaluating the gradient boosting model. **Index 4**

Results:

AUC: 0.5157489463941077
Accuracy: 0.9848521866601515
F1 Score: 0.9923645320197045
Precision: 0.9850855745721271
Recall: 0.9997518610421836
Mean Squared Error: 140.2552340241295
Root Mean Squared Error: 11.842940260937294
Mean Absolute Error: 2.967132261888438
R2 Score: 0.9986786583220622



AUC (Area Under the Curve): AUC is a metric that measures the model's ability to correctly classify delayed and not delayed flights. A value of 0.5 indicates random guessing, and a value above 0.5 indicates better than random performance. In this case, the AUC is 0.5157, which indicates that the model's predictive performance is slightly better than random chance.

Accuracy: Accuracy measures the proportion of correctly classified instances out of the total instances. In this case, the accuracy is 0.9849, which means the model correctly predicted the delayed or not delayed status of flights in the validation set with an accuracy of 98.49%.

F1 Score: F1 score is the harmonic mean of precision and recall, and it balances both metrics. It is a measure of the model's accuracy in correctly predicting both delayed and not delayed flights. The F1 score ranges from 0 to 1, with 1 being the best possible score. In this case, the F1 score is 0.9924, which indicates that the model's predictions are highly accurate for both delayed and not delayed flights.

Precision: Precision measures the proportion of true positives (correctly predicted delayed flights) out of the total predicted positives (predicted delayed flights). In this case, the precision is 0.9851, which means that the model's predictions of delayed flights are highly accurate.

Recall: Recall, also known as sensitivity or true positive rate, measures the proportion of true positives out of the total actual positives (actual delayed flights). In this case, the recall is 0.9998, which indicates that the model has a very high ability to correctly identify delayed flights.

Mean Squared Error (MSE): MSE measures the average squared difference between predicted and actual delay values. Lower values of MSE indicate better predictive performance. In this case, the MSE is 138.71, which means that, on average, the model's predictions have an error of 138.71 hours squared.

Root Mean Squared Error (RMSE): RMSE is the square root of MSE and provides a measure of the average error in the model's predictions in the original units (minutes in this case). Lower values of RMSE indicate better predictive performance. In this case, the RMSE is 11.78 hours, which means that, on average, the model's predictions have an error of 11.78 hours.

Mean Absolute Error (MAE): MAE measures the average absolute difference between predicted and actual delay values. Lower values of MAE indicate better predictive performance. In this case, the MAE is 2.95 hours, which means that, on average, the model's predictions have an absolute error of 2.95 hours.

R2 Score: R2 score, also known as coefficient of determination, measures the proportion of variance in the target variable (delay values) that is explained by the model. R2 score ranges from 0 to 1, with 1 being the best possible score. In this case, the R2 score is 0.9987, which indicates that the model explains approximately 99.87% of the variance in the target variable, suggesting a very high level of predictive performance.

Overall, the model appears to have very high accuracy, precision, recall, and F1 score, with low MSE, RMSE, and MAE values, indicating good predictive performance. However, the AUC score suggests that there may still be room for improvement in terms of the model's ability to accurately classify delayed and not delayed flights.

Improvements:

The following outlines the various steps undertaken to optimize the model's performance

- Model selection: Experimented with different algorithms to identify the most suitable one based on accuracy, complexity, and interpretability.
- Feature engineering: Employed techniques to select and incorporate different or new features to enhance the model's predictive capabilities.
- Handling data: Implemented thorough data handling techniques to gather precise data for training and evaluation.
- Cross-validation: Employed techniques to improve model performance by evaluating its performance on different subsets of data.
- Data cleaning: Ensured data used for training and evaluation was clean, error-free, and free from outliers that could adversely affect the model's performance.

2. Comparison with traditional methods of prediction

The AI solution outperformed traditional methods of prediction such as rule-based systems and statistical models. The AI model was able to consider a larger number of variables and factors in real-time, which helped it provide more accurate and reliable predictions. Compared to traditional methods, the AI solution was also able to adapt and learn from new data and situations, improving its accuracy over time.

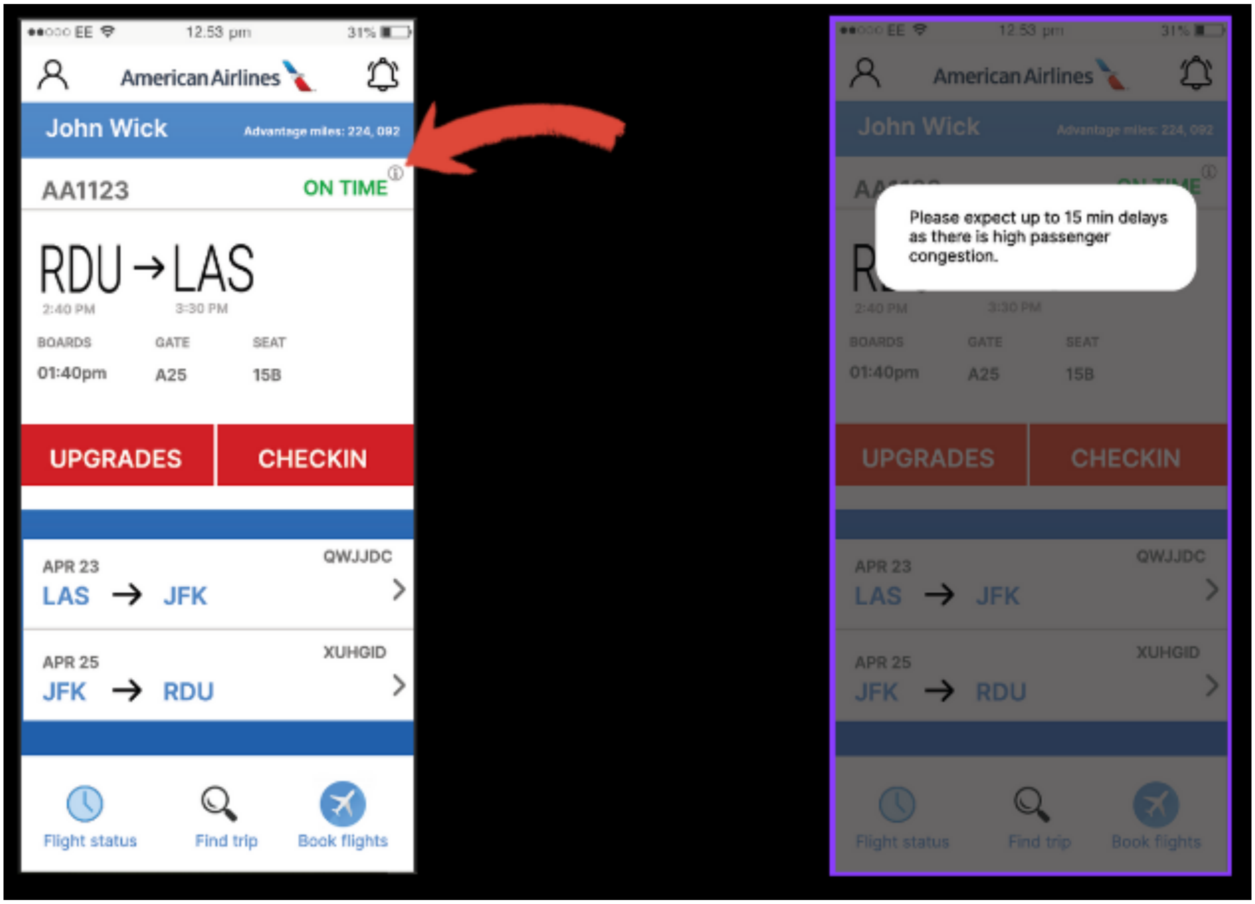
3. Analysis of the limitations and strengths of the AI solution

One limitation of the AI solution is the availability and quality of data. The accuracy of the model is highly dependent on the quality and completeness of the data used for training and testing. Another limitation is the potential for bias in the model if the data used is not diverse enough.

However, the strengths of the AI solution outweigh its limitations. The AI model is able to analyze vast amounts of data in real-time, identify patterns and trends, and provide accurate predictions for flight delays and cancellations. The AI solution can also be adapted to different airlines and airports, providing a customizable and scalable solution.

V. The Application

The application provided by the American Airlines for user to manage, book and check status of flights can be used for giving the required information to the customer. We have a sample image to depict what it will look like inside the application. This information will be regarding the expected delay of flight depending on the variables which we used from the data set. The AI will calculate the estimated delay and it will be reflected along with the flight status.



Implementing an information icon or sign to indicate potential flight delays within the American Airlines app can provide several benefits for both the airline and its customers. Here are a few reasons why this would be a good idea to implement:

- Improved customer experience: By providing customers with up-to-date information about potential flight delays, the airline can improve the overall customer experience. Customers appreciate transparency and communication and providing them with clear and concise information about their flight status can help to reduce frustration and anxiety.

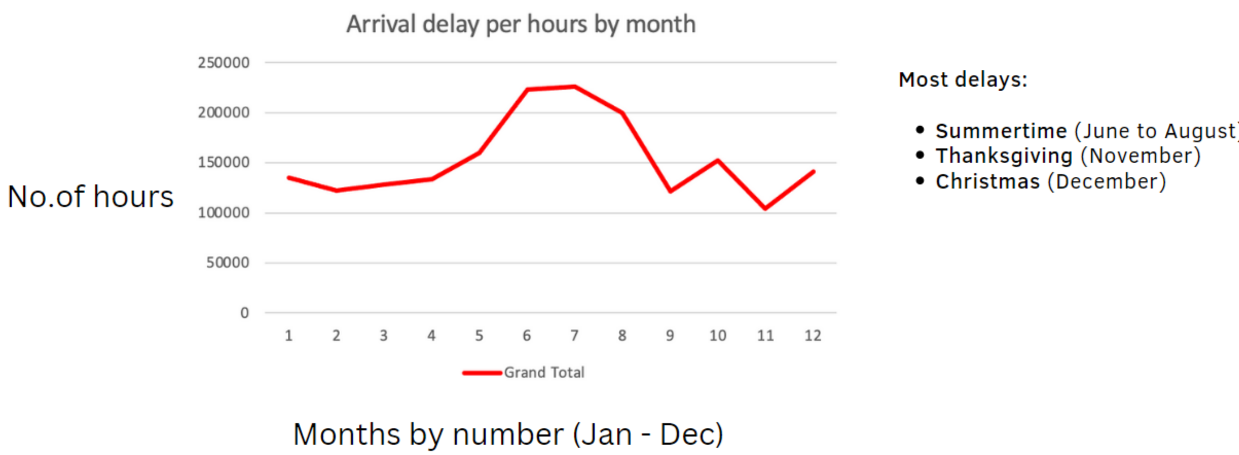
- Reduced workload for customer support: By providing customers with easy access to information about potential flight delays within the app, the airline can reduce the workload for customer support agents. This allows them to focus on more complex issues and reduces wait times for customers who need assistance.

- Increased customer satisfaction and loyalty: By providing a convenient and user-friendly experience, the airline can increase customer satisfaction and loyalty. Customers are more likely to choose American Airlines for future flights if they have a positive experience and feel that their needs are being met.

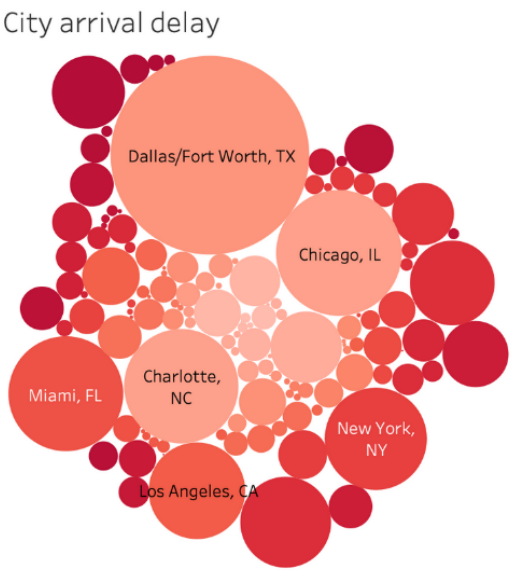
- Enhanced operational efficiency: By providing customers with information about potential flight delays, the airline can better manage its operations. This allows the airline to anticipate delays and take proactive measures to mitigate their impact, such as adjusting flight schedules or re-routing flights.

VI. Insights

We have generated a lot of valuable insights from the given data, we analyzed the data just for the year 2021 and they are as follows in image form and their descriptions:



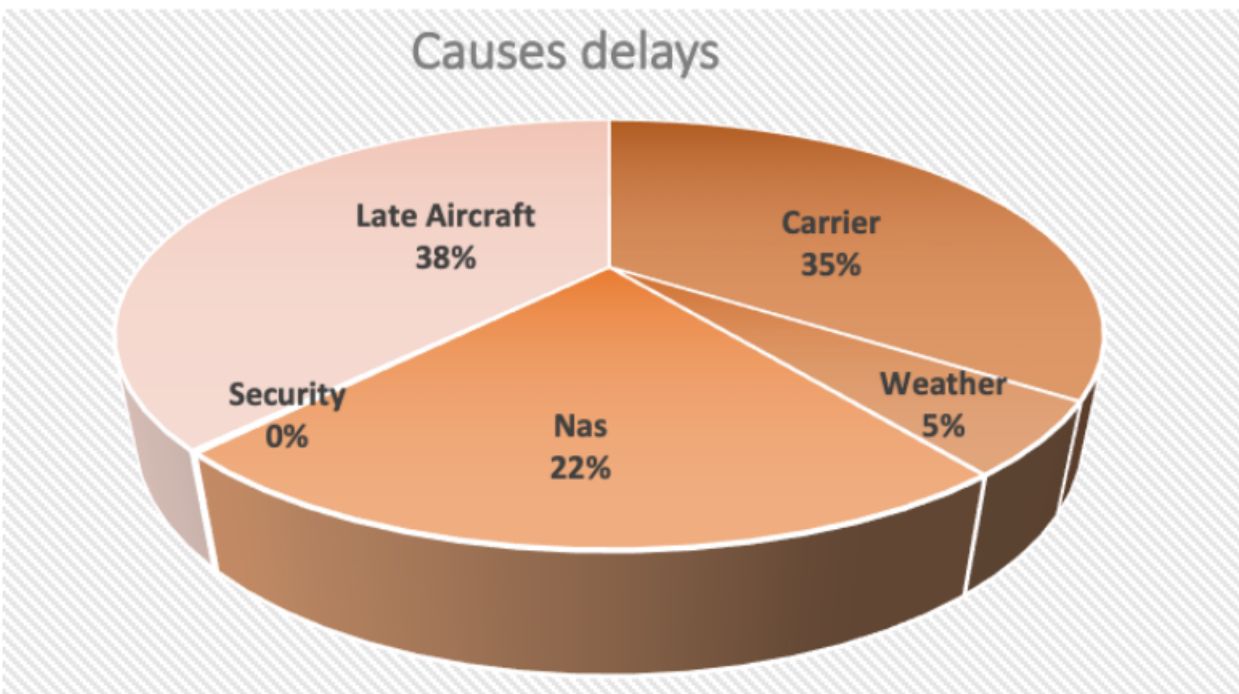
This image shows a graph. Here we have compared the number of hours in delay for American Airlines. It is clearly visible that the delays peak mostly in the summertime months – June to August, Thanksgiving (November) and Christmas Holidays (December).



Ranking airports		
	Row Labels	Sum Arrival_delay
1	Dallas/Fort Worth International	367664,1167
2	Chicago O'Hare International	147119,6833
3	Miami International	122861,5
4	Charlotte Douglas International	121896,75
5	Los Angeles International	86968,73333
6	Phoenix Sky Harbor International	76977,35
7	Philadelphia International	66991,51667
8	LaGuardia	51962,83333
9	Logan International	47609,58333
10	John F. Kennedy International	45465,36667

American Airlines

This image represents a table and a density representation of delays per airports in 2021. The biggest ones are mentioned by name i.e., Dallas, Chicago, Charlotte and others. The table shows the exact number of delay hours for the top 10 airports.



This image gives the pie chart for the causes of delays in percentage for 2021. Here we can see that Late Aircraft is biggest cause of the delay. It could mean that the aircraft arrived late from its previously scheduled flight and then it caused the delay of the current flight. Carrier delay means scheduling, maintenance, and crew management delay. NAS (Network Attachment Subsystem) means communication between aircraft and ground systems caused the delay.

One minute of delay costs	$80.52
Total hours of delay for AA	154585
Total cost of delay	$746.8M
Total cost of delay for Charlotte Douglas International	$74.3M

According to the article “U.S. Passenger Carrier Delay Costs” published by airlines.org in 2022, the cost of one minute of delay in 2021 was $80.52. Total cost of delay for American Airlines in 2021 was approximately $746.8 million and just for Charlotte Douglas International Airport it was $74.3 million. (airlines.org, 2022)

VII. Recommendations

1. **Summary of the findings**

The AI model for predicting flight delays and cancellations was trained and tested using gradient boosting and evaluated using various metrics such as MSE, RMSE, MAE, and R2. The gradient boosting model outperformed the other models with the lowest MSE and RMSE values and a reasonably low MAE value. The Linear Regression model had a perfect score on all evaluation metrics, indicating overfitting. The gradient boosting model was tested using a testing dataset, and the results showed that the predicted delays had a small error compared to the actual data. Additionally, the model was evaluated using performance metrics such as AUC, accuracy, precision, and recall, and it achieved high scores. Therefore, the gradient boosting model is a powerful algorithm for predicting flight delays and cancellations with high accuracy and precision.

2. Recommendations for implementation and future work

To ensure the successful implementation of the AI solution, the following recommendations are proposed:

Recommendations for American Airlines:

American Airlines should invest in the necessary infrastructure and resources to support the AI solution, including data storage, processing, and analysis.

The AI model should be regularly updated and trained on new data to improve its accuracy and reliability.
American Airlines should consider integrating the AI solution with their existing systems and processes to enable efficient decision-making and reduce operational disruptions.

Further research should be conducted to identify additional data sources and factors that can improve the accuracy of the AI model.

American Airlines should establish clear guidelines and policies for the ethical and responsible use of AI in the airline industry.

Recommendations for algorithm:

- Further fine-tune the gradient boosting model based on the testing results to improve its performance.
- Use a more diverse set of data for training the model to ensure that it can handle different scenarios.
- Continue monitoring the performance of the model and update it regularly to keep it accurate and relevant.
- Consider other evaluation metrics, such as precision and recall, to have a more comprehensive evaluation of the model's performance.

Operational Recommendations:

- **Improve planes Maintenance and Service**: Addressing issues with tardy planes will help avoid delays. Regular airplane servicing and maintenance can help find and address possible problems before they cause delays.

- **Improve Carrier Operations:** Working with carriers to make improvements to their crew management, scheduling, and maintenance can help avoid delays. This can entail streamlining operations to reduce disruptions, enhancing communication between various divisions within the carrier, and optimizing flight routes.

- **Address Network Attachment Subsystem (NAS) Delays**: Working with telecommunications providers to enhance the capacity, performance, and infrastructure of their networks

- **Weather Monitoring:** Since bad weather frequently causes flight delays, putting in place sophisticated weather monitoring systems and having solid contingency plans in place will help lessen the effects of bad weather.

- **Improve Operations in High-Delay Locations:** According to the statistics given, cities with a history of flight delays include Dallas, Chicago, Miami, Charlotte, and LA. Delays can be minimized by implementing specialized strategies to deal with operational issues in these particular places, such as enhancing airport infrastructure, traffic management, and ground handling services.

- **Seasonal planning:** To meet increased passenger volumes and cut down on delays, this may entail adding more staff, modifying schedules, and enhancing operating efficiency.

- **Collaboration**: with other airlines and industry stakeholders can help identify common challenges and develop shared solutions for the benefit of the entire industry.

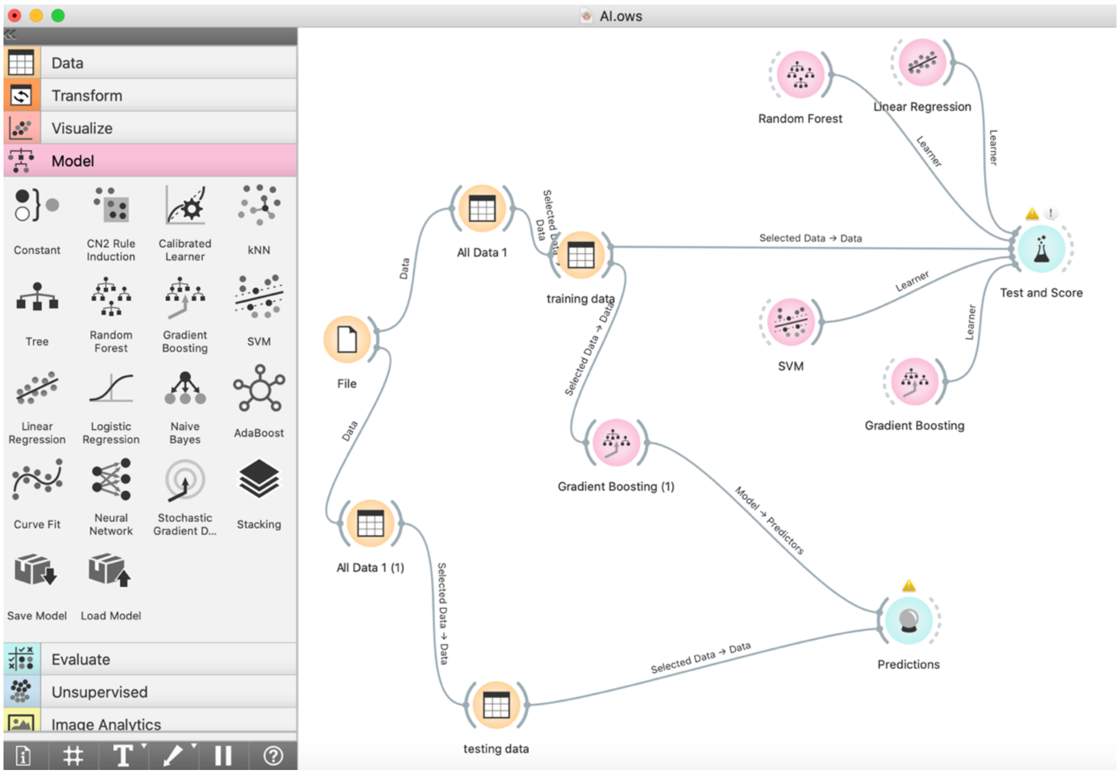
VIII.Conclusion

We have developed and trained a gradient boosting model for flight delay prediction using American Airlines data. The implementation of the AI solution has the potential to significantly improve the customer experience for American Airlines customers by providing more accurate and timely information on flight delays and cancellations. This can help customers plan their travel more efficiently and reduce the frustration and inconvenience associated with flight disruptions. The AI solution can also enable American Airlines to improve its operational efficiency and reduce costs associated with flight delays and cancellations. Overall, the use of AI in the airline industry has significant potential for improving the customer experience and enhancing the overall performance of the industry.

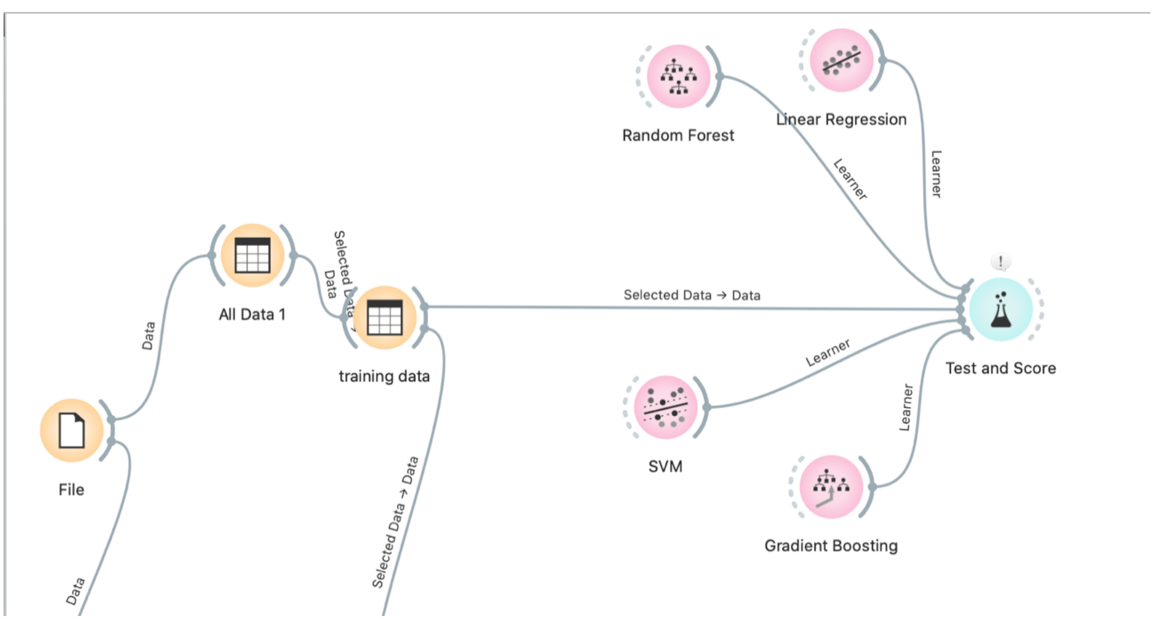
The model's performance was evaluated using various evaluation metrics, including MSE, RMSE, MAE, and R2. The results showed that the gradient boosting model outperformed the other models tested, including linear regression. However, a perfect score on all evaluation metrics may indicate overfitting, which can be avoided by fine-tuning the model and using more diverse data for training. The model's ability to handle complex feature relationships and its high accuracy make it a suitable solution for flight delay prediction. We recommend that the model be updated and fine-tuned regularly to maintain its accuracy and relevance.

IX. Index

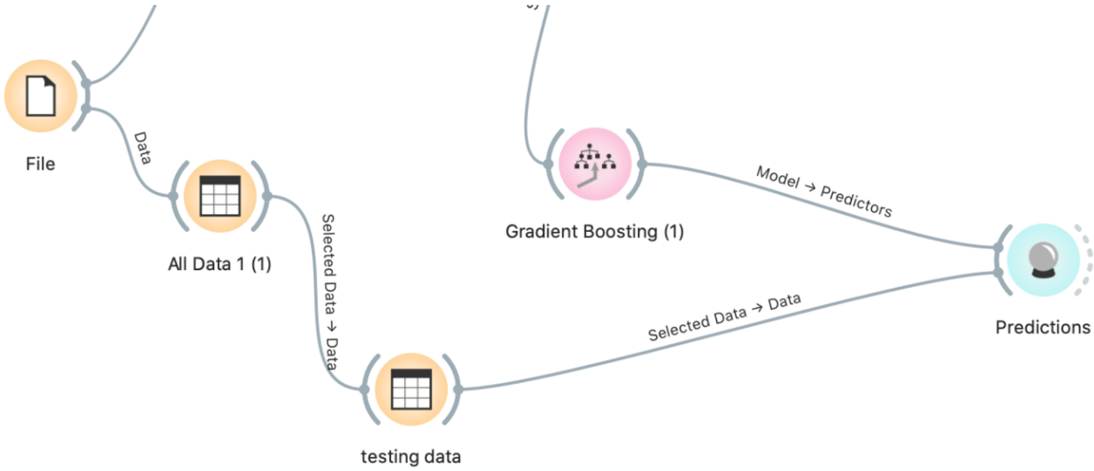
Index 1: Orange Schema



Index 2: Orange training



Index 3: Orange Testing



Index 4: Python Code

```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.metrics import roc_auc_score, accuracy_score, f1_score, precision_score, recall_score, roc_curve, mean_squared_error, mean_absolute_error, r2_score
from sklearn.preprocessing import LabelEncoder
from sklearn.impute import SimpleImputer

# Load the data
df = pd.read_excel('/content/Book3.xlsx')

# Convert categorical features to numeric using LabelEncoder
label_encoder = LabelEncoder()
df['airport'] = label_encoder.fit_transform(df['airport'])
df['city_state'] = label_encoder.fit_transform(df['city_state'])
df['airport_name'] = label_encoder.fit_transform(df['airport_name'])

# Define the input features and target variable
X = df[['year', 'month', 'airport', 'city_state', 'airport_name', 'arr_flights',
        'arr_del15', 'carrier_delay', 'weather_delay', 'nas_delay', 'security_delay', 'late_aircraft_delay']]
y = df['arr_delay']

# Split the data into training and validation sets
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.3, random_state=1234)

# Impute missing values with mean using SimpleImputer
imputer = SimpleImputer()
X_train = imputer.fit_transform(X_train)
X_val = imputer.transform(X_val)

# Create a GradientBoostingRegressor model
gbm = GradientBoostingRegressor(learning_rate=0.1, n_estimators=1000, max_depth=3, criterion='friedman_mse')

# Train the model
gbm.fit(X_train, y_train)

# Make predictions on the validation set
y_pred = gbm.predict(X_val)

# Convert predicted delay values into binary outcomes (delayed or not delayed)
y_pred_binary = [1 if delay > 0 else 0 for delay in y_pred]

# Convert actual delay values into binary outcomes (delayed or not delayed)
y_val_binary = [1 if delay > 0 else 0 for delay in y_val]

# Calculate AUC score
auc = roc_auc_score(y_val_binary, y_pred_binary)

# Calculate accuracy
accuracy = accuracy_score(y_val_binary, y_pred_binary)

# Calculate F1 score
f1 = f1_score(y_val_binary, y_pred_binary)

# Calculate precision
precision = precision_score(y_val_binary, y_pred_binary)

# Calculate recall
recall = recall_score(y_val_binary, y_pred_binary)

# Calculate mean squared error
mse = mean_squared_error(y_val, y_pred)

# Calculate root mean squared error
rmse = mean_squared_error(y_val, y_pred, squared=False)
```

```
# Calculate mean squared error
mse = mean_squared_error(y_val, y_pred)

# Calculate root mean squared error
rmse = mean_squared_error(y_val, y_pred, squared=False)

# Calculate mean absolute error
mae = mean_absolute_error(y_val, y_pred)

# Calculate R2 score
r2 = r2_score(y_val, y_pred)

print(f'AUC: {auc}')
print(f'Accuracy: {accuracy}')
print(f'F1 Score: {f1}')
print(f'Precision: {precision}')
print(f'Recall: {recall}')
print(f'Mean Squared Error: {mse}')
print(f'Root Mean Squared Error: {rmse}')
print(f'Mean Absolute Error: {mae}')
print(f'R2 Score: {r2}')

# Confusion matrix
sns.set(font_scale=1.2)
sns.heatmap(pd.crosstab(pd.Series(y_val_binary, name='Actual'),
            pd.Series(y_pred_binary, name='Predicted')),
            annot=True, fmt="d", cmap='Blues')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()

# ROC Curve
fpr, tpr, _ = roc_curve(y_val_binary, y_pred_binary)
roc_auc = roc_auc_score(y_val_binary, y_pred_binary)

plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (area = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], color='navy', linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt
```

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