Machine Learning - Project Report Document

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Batch	AI Elite 18
Project Name	Flight Ticket Price Prediction
Project Domain	Predictive analytics
Type of Machine Learning	Supervised ML
Type of Problem	Regression
Project Methodology	CRISP-DM
Stages Involved	• Data Collection and Understanding • Data Preparation • Model Building • Model Training • Model Evaluation • Model Deployment

Business Understanding:

The concept of flight price prediction involves analyzing historical data and various factors that influence the cost of airline tickets, such as the airline, departure date, booking class, and other relevant features. The goal is to predict the fare of a flight ticket for customers, enabling them to make informed decisions and potentially save money on their travel expenses.

The airline industry is highly competitive and dynamic, with ticket prices fluctuating based on demand, seasonality, fuel prices, and other factors. By leveraging predictive models, airlines and travel agencies can optimize pricing strategies, enhance customer satisfaction, and increase revenue.

In this context, flight price prediction serves multiple purposes:

- **Customer Decision-Making:** Helping customers find the best deals and plan their travel budget effectively.
- **Revenue Management:** Assisting airlines in setting competitive prices while maximizing revenue.
- **Market Analysis:** Providing insights into market trends and customer preferences.

Problem Statement:

This project aims to develop a model that can predict the fare of a flight ticket based on features such as airline, departure date, booking class, and other relevant factors. This will enable more accurate pricing strategies and enhance customer satisfaction by providing fare predictions.

Here are some potential business constraints:

- Regulatory Compliance: Ensuring the model adheres to aviation industry regulations and pricing guidelines.
- Data Privacy and Security: Protecting customer data and maintaining privacy in compliance with relevant laws.
- Resource Limitations: Managing computational resources and time constraints for model training and deployment.
- Accuracy and Reliability: Striving for high accuracy in predictions while maintaining model reliability.
- Interpretability: Balancing the complexity and interpretability of the model to ensure stakeholders understand pricing variations.
- Ethical Considerations: Ensuring fair pricing practices and avoiding any discriminatory pricing based on customer profiles.
- Competitive Landscape: Staying competitive by adapting to market trends and competitor pricing strategies.

Stage 1: Data Collection and Understanding

a) **Data Collection:** The dataset source for this project was Kaggle. The Data was collected in two parts(datasets): one for economy class tickets and another for business class tickets. A total of 300261 distinct flight booking options was extracted from the website Easemytrip for flight travel between India's top 6 metro cities. The data contains information on flights for 50 days, from February 11th to March 31st, 2022. The both datasets were later combined into a single dataset after doing cleaning.

b) **Data Understanding:**

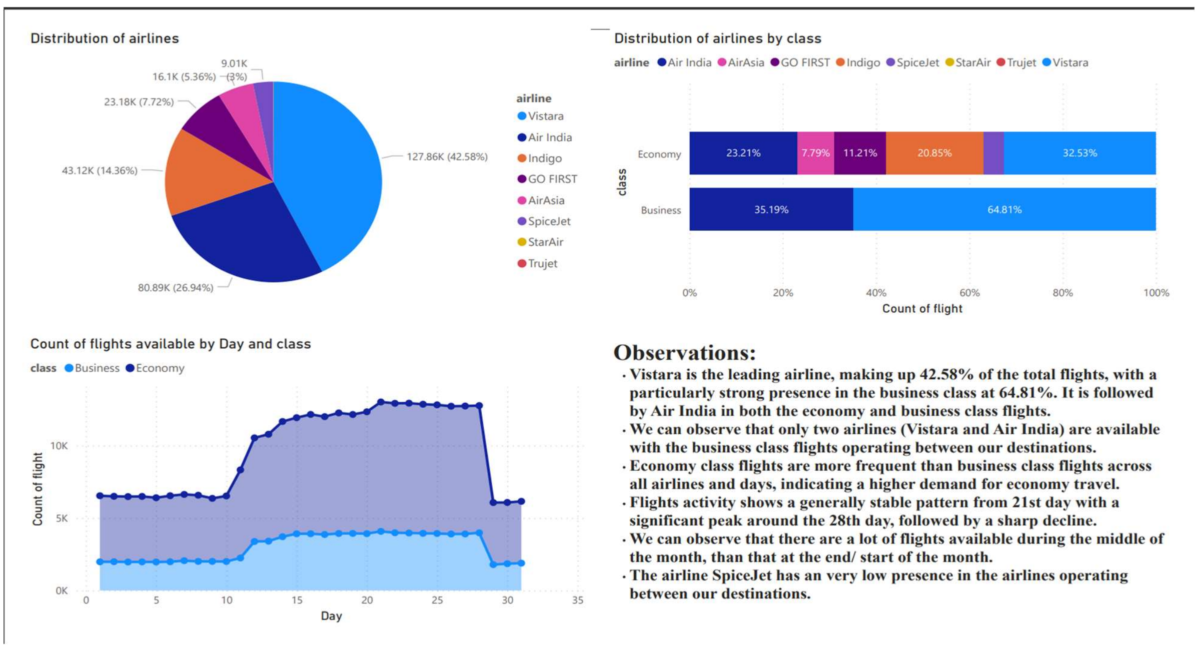
1. Airline: The name of the airline company. It is a categorical feature having 6 different airlines.
2. Flight: Information regarding the plane's flight code. It is a categorical feature.
3. Source City: The city from which the flight takes off. It is a categorical feature having 6 unique cities.
4. Departure Time: A derived categorical feature created by grouping time periods into bins. It stores information about the departure time and has 4 unique time labels.
5. Stops: A categorical feature with 3 distinct values that stores the number of stops between the source and destination cities.
6. Arrival Time: A derived categorical feature created by grouping time intervals into bins. It has 4 distinct time labels and keeps information about the arrival time.
7. Destination City: The city where the flight will land. It is a categorical feature having 6 unique cities.
8. Class: A categorical feature that contains information on seat class; it has two distinct values: Business and Economy.
9. Duration: A continuous feature that displays the overall amount of time it takes to travel between cities in hours.
10. Days Left: A derived characteristic calculated by subtracting the trip date from the booking date.
11. Price: The target variable that stores information about the ticket price.

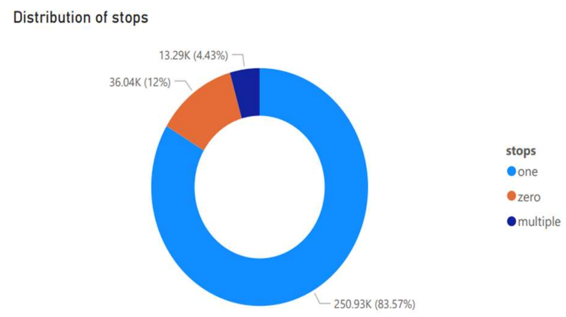
S No	Feature Name	Data Type
1	Date	Object
2	Airline	Object
3	Flight	Object
4	From	Object
5	Departure time	Object
6	Stops	Object
7	Destination	Object

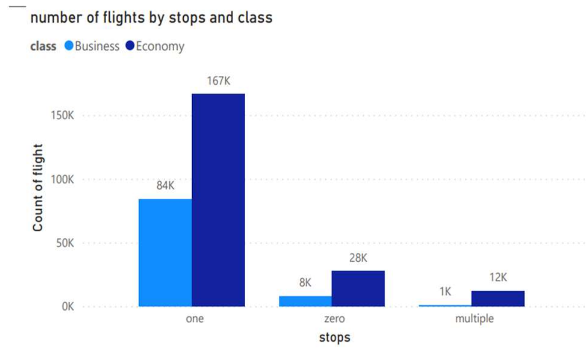
8	Arrival time	Object
9	Class	Object
10	Duration	Float64
11	Days left	Int64
12	Price	Float64

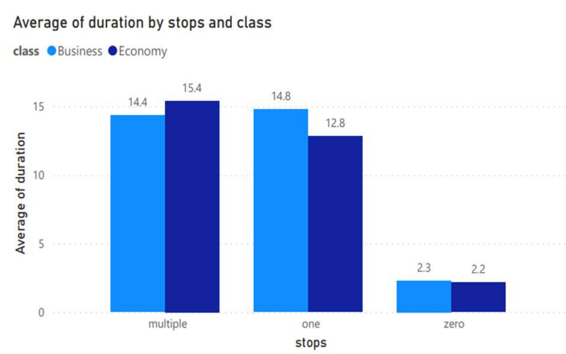
Stage 2: Data Preparation

a) Exploratory Data Analysis:



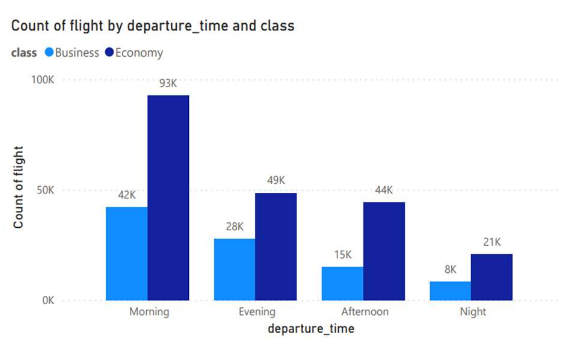


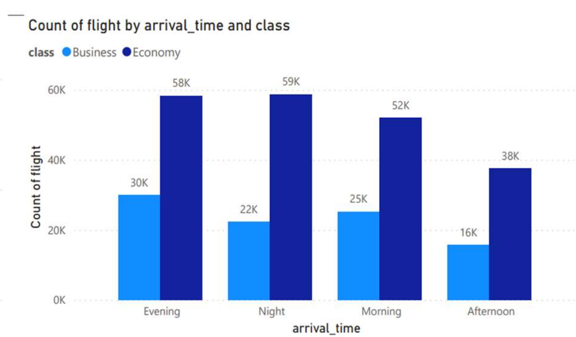


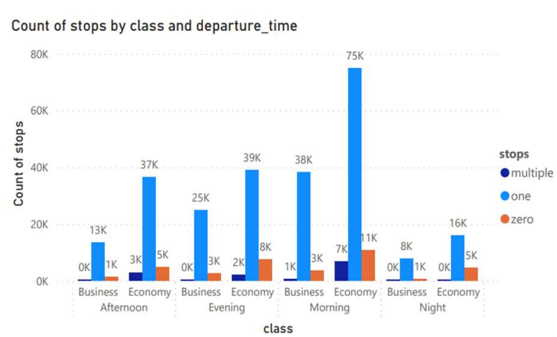


Observations:

- We can observe that majority of the flights with one stop are the most common, making up 83.57% of the total.
- Direct (zero stop) flights account for 12% of the total, while multiple-stop flights are rare, comprising only 4.43% of the total.
- Flights with multiple stops have the longest average duration for economy class, while flights with single stop have the longest average duration for the business class.
- Direct flights have the shortest duration, with similar durations for both business and economy classes.



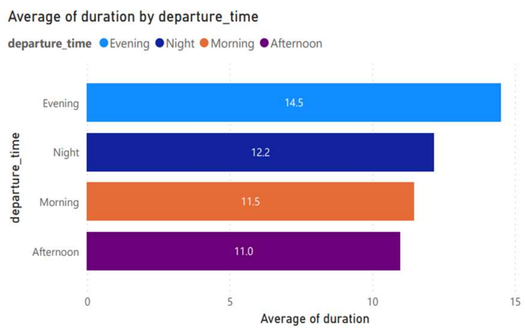


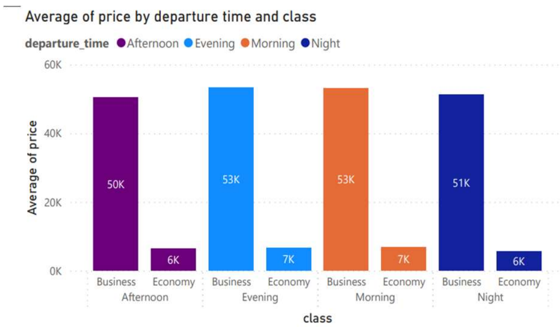


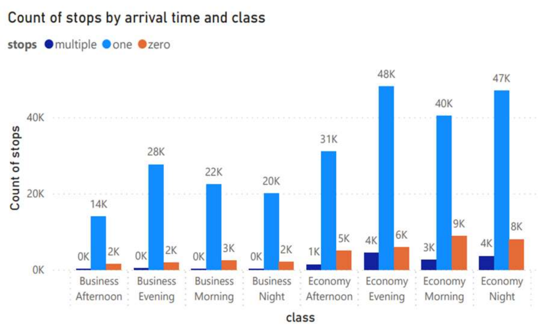
Observations:

- The highest no. of flights by departure time and class is for economy class in the morning, with 93K flights. This significantly outnumbers any other category.
- The lowest no. of flights by departure time and class is for business class in the night, with 8K flights.
- The evening arrival time sees the highest count of flights across both classes, with a total of 58K flights for economy and 30K flights for business, totaling 88K flights.
- Business class flights are most frequent in the evening in terms of arrivals. While the economy class flights are almost equal during evening and nights in terms of arrival.
- The economy class flights have a lot of stops which depart in the morning and the least during the night.

INNOMATICS RESEARCH LABS

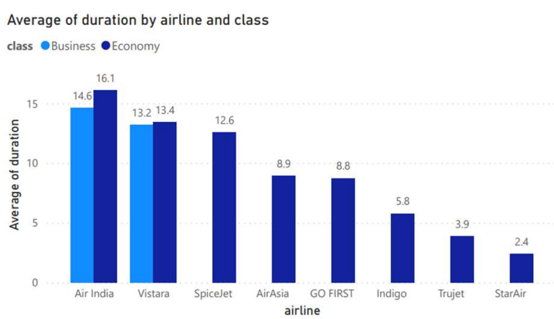


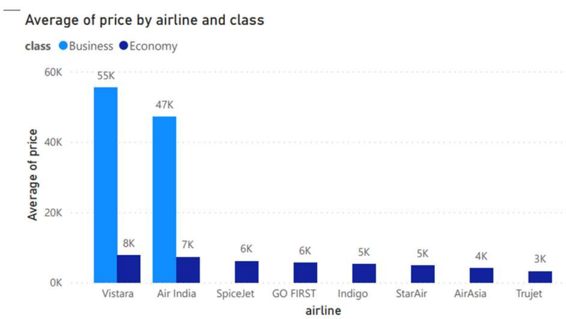


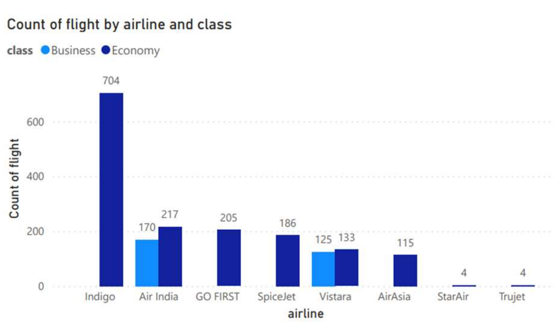


Observations:

- Flights departing in the evening have the highest average duration of 14.5 hours, significantly longer than flights at other times of the day.
- Flights departing in the morning and afternoon have the shortest average durations, at 11.5 hours and 11.0 hours respectively.
- The average price for business class flights is fairly consistent across departure times, ranging from 50K to 53K. In contrast, economy class flights are consistently cheaper, averaging between 6K and 7K across all times.
- Economy class flights in the evening and night have a high count of stops, with evening flights having 48K stops and night flights having 47K stops. In contrast, business class flights have fewer stops, with lowest no. of multiple-stop flights recorded.

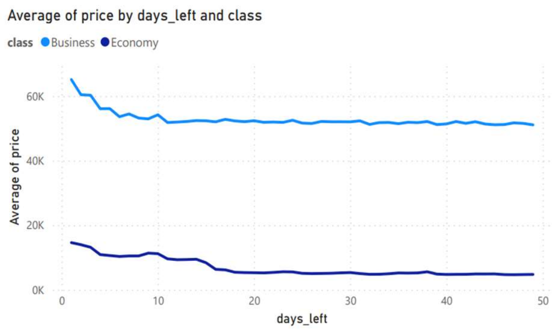


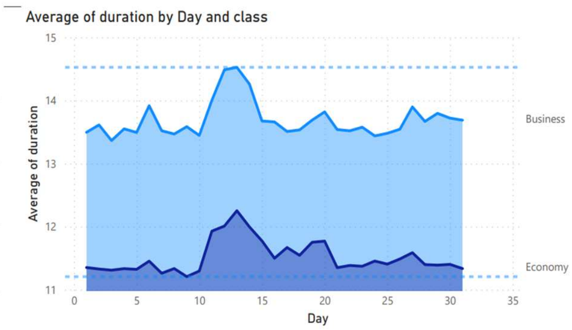


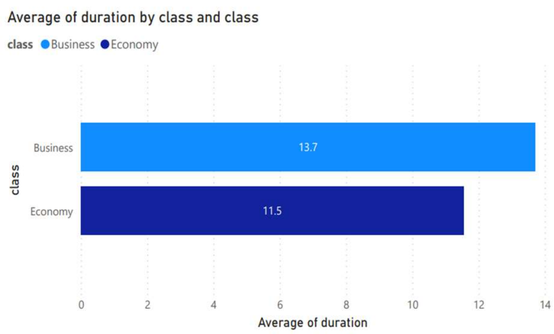


Observations:

- Vistara has the highest average duration for economy class flights, with an average of 16.1 hours. This is higher than any other airline for either class.
- The average price for business class flights on Vistara is the highest, at 55K. This is significantly higher compared to other airlines, with the next highest being Air India at 47K. While they're at a similar range in economy class flights.
- StarAir and Trujet have the shortest average durations for economy class flights, with StarAir at 2.4 hours and Trujet at 3.9 hours.
- Across all airlines, economy class flights have significantly lower average prices compared to business class flights. The average price for economy class flights remains below 8K for all airlines, whereas business class prices are much higher in Vistara and Air India.
- The StarAir and Trujet have the lowest count of flights with different travel routes. The Indigo airlines have the highest no. of flight routes among all the airlines. It's followed by Air India with the 2nd highest highest no. of travel routes available.

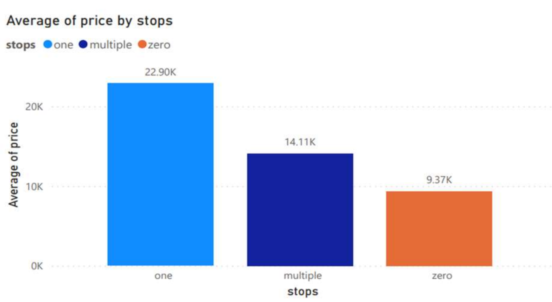


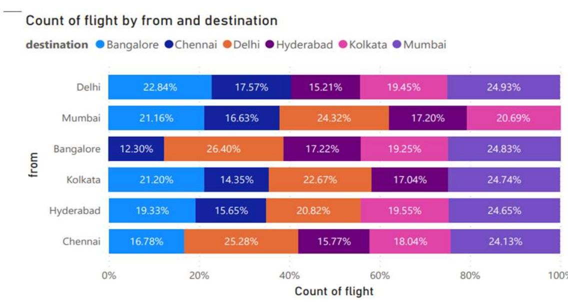


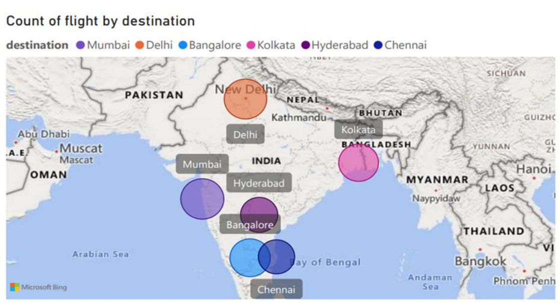


Observations:

- The average price of flights decreases as the days left until departure increase. This trend is evident for both business and economy classes, with a steeper decline for business class prices.
- Business class flights consistently have higher average prices compared to economy class across all days left until departure.
- On average, business class flights have a longer duration (13.7 hours) compared to economy class flights (11.5 hours). This might be due to the no. of stops for the respective flights.
- The average duration of flights varies significantly day-to-day for both business and economy classes. We can observe that it get longer in the middle of the month around 10th to 16th.
- While both classes show variations in flight duration over days, economy class durations are more consistent and show fewer fluctuations compared to business class durations.



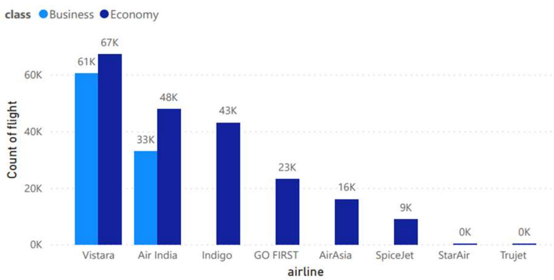




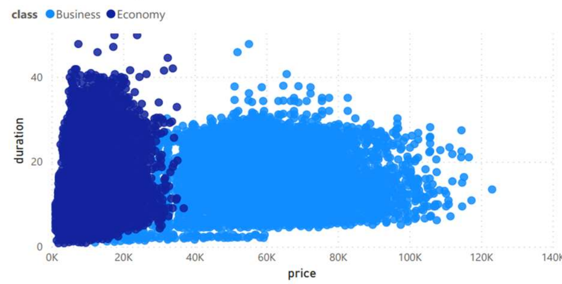
Observations:

- Flights with one stop have the highest average price, at 22.9K. This is significantly higher compared to flights with multiple stops (14.11K) and non-stop flights (9.37K).
- A notable percentage of flights from Bangalore are destined for Delhi, with 26.40% of flights heading there. This is the highest percentage for any destination from Bangalore.
- A notable percentage of flights from Bangalore are destined for Chennai, with 12.30% of flights heading there. This is the lowest percentage for any destination from Bangalore.
- Delhi receives a high proportion of flights from multiple origins, with notable percentages from Bangalore (26.40%), Chennai (25.28%), and Mumbai (24.32%).
- The geographical distribution plot shows that Mumbai and Delhi are major hubs with significant flight activity. They have a substantial number of flights to and from various destinations, indicating their importance in the flight network.
- The flights to Mumbai from different locations have an almost same distribution maintaining consistency.

Count of flight by airline and class



price vs duration by class



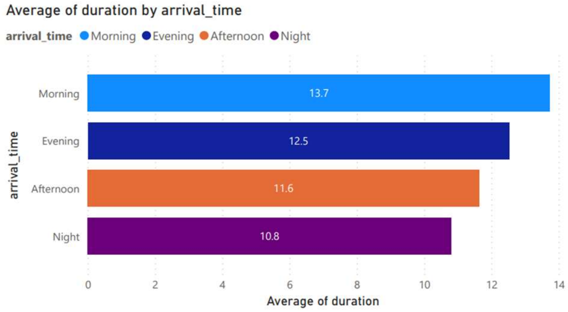
descriptive statistics table on price based on the departure location to destination

from	No. of Flights	Average price	Max	Median	Min	S.D of price
Mumbai	60903	21481.71	114523	7413	1890	23393.42
Kolkata	46347	21746.24	123071	7958	2436	23439.72
Hyderabad	40860	20133.24	115211	6799	1543	21714.79
Delhi	61345	18950.98	117307	6840	1998	20920.00
Chennai	38700	21995.34	114704	7846	1105	23526.92
Bangalore	52106	21455.88	111883	7488	1603	23165.99
Total	**300261**	**20883.72**	**123071**	**7425**	**1105**	**22695.87**

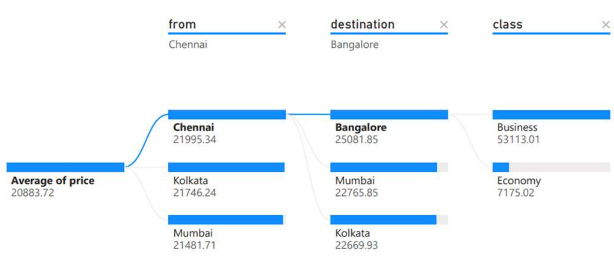
Observations:

- Vistara operates the highest number of flights overall, with 67K economy flights and 61K business flights, making it the leading airline in terms of flight count.
- Air India and Indigo also have a substantial number of flights, with Air India operating 48K economy and 33K business flights, and Indigo operating 43K economy flights. This positions them as significant players in the airline market.
- There is a visible clustering of flight durations around shorter times, with economy flights generally priced lower than business flights. However, some business flights have much higher prices, indicating a broader price range for this class.
- The table reveals significant variability in flight prices across different cities. Chennai has the highest average price at 21,995.34, followed by Kolkata and Mumbai. Delhi has the lowest average price at 18,950.98 among the major cities listed.
- The standard deviation of prices is relatively high for all cities, indicating considerable price variability. Kolkata has the highest standard deviation (23,439.72), followed closely by Chennai and Mumbai, suggesting a wide range of pricing options within these cities.

Average of duration by arrival_time

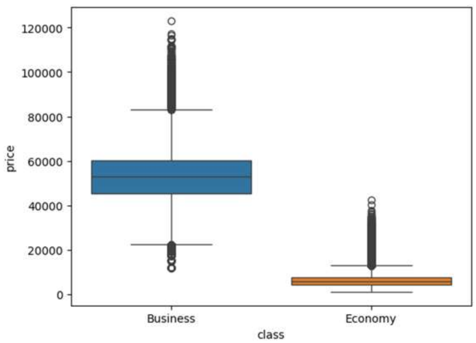


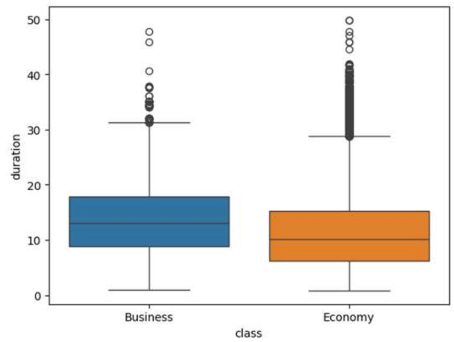
Average of price by class



Observations:

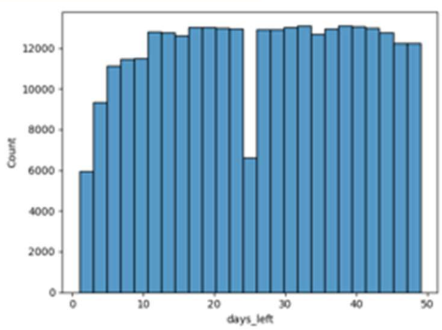
- From the bar graph we can observe that on a most of the flights arrive either in the morning or the evening, meaning it's the most crowded times in the airport.
- The business class flights cost around 8 times more than economy class flights on an average. It can be a major factor to be considered based on the urgency of the person.
- The tree diagram shows the avg. costs of flights along with their duration when hovered from one place to another with in detail of travelling class division too.





The outliers in the price column are present primarily because all identified high-priced flights are in the Business class, have either one or multiple stops, are operated exclusively by Vistara, majority are departing in the morning or evening and some are booked close to the departure date, all of which contribute to significantly higher prices. So we can't exclude the outliers as they are true outliers.

From the above we can observe that the flight durations contains outliers and these outliers in the flight duration column are valid and likely caused by real-world variations in flight operations, such as the number of stops, specific flight routes, layover times, and the types of aircraft used. So we can't exclude the outliers as they are true outliers.



destination from	Bangalore	Chennai	Delhi	Hyderabad	Kolkata	Mumbai
Bangalore	0	6410	13756	8971	10029	12940
Chennai	6493	0	9783	6103	6983	9338
Delhi	14012	10780	0	9328	11934	15291
Hyderabad	7898	6395	8507	0	7987	10073
Kolkata	9824	6653	10506	7897	0	11467
Mumbai	12885	10130	14809	10477	12602	0

- **The histogram of the days_left variable from the flight dataset reveals a bimodal distribution with peaks around 20 and 30 days before departure, and a noticeable dip around the 25-day mark, indicating fewer flights at that point.**
- **The highest no. of flights are flying from Delhi to Mumbai, this might be because they're quite the famous cities also known as capital and financial capital of India.**
- **The lowest count of flights are from Chennai to Hyderabad, this might be because of them being close to each other, leading to the availability of other kinds of transportations.**

	duration	days_left	price
duration	1.000000	-0.039105	0.204473
days_left	-0.039105	1.000000	-0.091917
price	0.204473	-0.091917	1.000000

- **Above table shows the correlation of the different numerical columns in our dataset. We can observe that price and duration have a weak positive relation, also that price and days_left have a weak negative correlation.**
- **From the right table we can observe the flight tickets cost with respect to each of the base city to the destination city. It contains the values like "min", "max", "mean", "median" and "Standard deviation" of the price based on the different locations the flight travels between.**

from	destination	min	max	mean	median	std
Bangalore	Chennai	1603.0	90720.0	23321.850078	9241.0	22573.185689
	Delhi	2723.0	111883.0	17723.313972	7164.0	19746.484106
	Hyderabad	1694.0	83239.0	21152.051053	7813.0	21861.177859
	Kolkata	3026.0	105168.0	23498.234221	8112.0	24630.560155
	Mumbai	2150.0	103819.0	23127.231376	7113.0	25887.165127
Chennai	Bangalore	1443.0	107597.0	25081.850454	10469.0	23405.422526
	Delhi	2051.0	103683.0	18981.863948	7352.0	21946.879653
	Hyderabad	1105.0	92752.0	21591.345404	7373.0	22866.927328
	Kolkata	2359.0	104624.0	22669.932407	8394.0	23667.149966
	Mumbai	1830.0	114704.0	22765.849647	8233.0	25118.401202
Delhi	Bangalore	3090.0	85353.0	17880.216315	6642.0	19904.508234
	Chennai	1998.0	104466.0	19369.881354	7425.0	22127.553940
	Hyderabad	2022.0	114507.0	17347.288379	6109.0	18768.239479
	Kolkata	2480.0	117307.0	20566.409418	7084.0	23655.844456
	Mumbai	2281.0	95657.0	19354.405336	7262.0	19776.397176
Hyderabad	Bangalore	1755.0	97767.0	21245.945429	6855.0	22174.741408
	Chennai	1543.0	95208.0	21848.065989	7702.0	22527.946093
	Delhi	2200.0	86203.0	17242.639473	6138.0	18547.945651
	Kolkata	2056.0	97381.0	20823.893201	7767.0	22237.613504
	Mumbai	2250.0	115211.0	20065.715179	6633.0	22633.659515
Kolkata	Bangalore	3465.0	105638.0	22744.808428	8111.0	24130.762785
	Chennai	2966.0	95183.0	23660.361040	8589.0	23371.419897
	Delhi	2994.0	123071.0	19422.354559	6723.0	22693.238883
	Hyderabad	2436.0	114705.0	21500.011397	8467.0	22690.671624
	Mumbai	3379.0	110936.0	22078.883579	7958.0	23887.604966
Mumbai	Bangalore	2074.0	114523.0	23147.873807	7192.0	25900.493645
	Chennai	1890.0	111964.0	22781.899112	8148.0	24690.486578
	Delhi	2336.0	111437.0	18725.320008	6300.0	19493.523862
	Hyderabad	2105.0	99677.0	20992.128567	7584.0	22807.139498
	Kolkata	2835.0	100909.0	22379.146723	7518.0	23998.184785

Based on the observations from the various plots and data provided, here are some recommendations for booking flight tickets:

Recommendations:

Book Economy Class for Cost Savings:
- Economy class consistently has lower prices compared to business class across all airlines and times of day. If budget is a priority, opt for economy tickets.

Optimal Departure and Arrival Times:
- Morning and evening flights are the most common, but afternoon flights have the shortest average duration (11.0 hours). If duration is a concern, consider booking flights that depart in the afternoon.
- For arrivals, evening flights tend to have the highest counts, but if avoiding busy times is a priority, consider arriving in the morning or afternoon.

Choosing Airlines:
- Vistara and Air India offer the highest number of flights and a good balance of price and duration. For a balance between frequency and cost, these airlines are recommended.
- For the lowest prices, consider airlines like GO FIRST, Indigo, and AirAsia, but be aware that these may also have longer average durations and fewer flight options.

Direct vs. Stopover Flights:
- Direct flights (zero stops) are generally cheaper than flights with one or multiple stops. If cost is a major factor, prioritize booking direct flights.
- Multiple stops significantly increase the duration and sometimes the cost of the flight. If possible, avoid flights with multiple stops.

Booking Based on City and Destination:
- Flights to and from Chennai and Kolkata have higher average prices. If flying to these destinations, book well in advance to secure the best rates.
- For destinations like Delhi and Hyderabad, which have lower average prices, you might have more flexibility in booking without as much of a price increase closer to the departure date.

Leverage Price and Duration Insights:
- For business travelers prioritizing time, choosing business class might be more beneficial despite the higher cost, especially during morning or evening times.
- For personal travel, where budget might be more critical, evening flights in economy class can offer a good balance between cost and convenience.

Consider Flight Durations:
- Flights from airlines like Vistara and Air India have longer average durations but might provide better service and reliability. If comfort and reliability are important, these airlines are preferable.
- For shorter durations, SpiceJet and AirAsia can be good choices, but ensure you check for any additional costs or less frequent flights.

Flexibility with Stops:
- If you are flexible with travel times and can manage longer travel durations, flights with multiple stops can sometimes be cheaper. However, if time is a constraint, prioritize direct flights even if they are slightly more expensive.

Book Early for Peak Times:
- During peak travel seasons or times (e.g., holidays, weekends), flights, especially in the morning and evening, fill up quickly. Booking early can help you secure better prices and preferred times.
- Booking at-least 10 days early can help you cut down the costs for any pre-planned occasions. Booking the flights at the middle of the month can be budget friendly as more flights are available at that time.

S No	Type	Feature Names	Observation
1	Missing Values	NA	NA
2	Duplicates	All columns	There exist 3195 duplicate datapoints in the dataset.
3	Outliers	Duration, Price	There exist outliers in these columns.

b) Data Cleaning/wrangling:

S no	Type of Cleaning	Technique	Feature Name	Reason
1	Duplicate value	Drop	All columns	To maintain data consistency and accuracy as they don’t carry any useful information. Dropped 3195 datapoints.
2	Encoding	Binary Encoder	Airline, From. Departure time, Stops, Destination, Arrival time, Class	Used Binary Encoding since the data in these categorical columns are nominal with a high cardinality ranging from 4 to 8.
3	Scaling	Robust Scaling	Duration, Days left	Used Robust Scaling since there exists outliers in the column “Duration” and robust scaler handles the outliers better. Since they contain true outliers.

c) Feature Selection:

S no	Removed Feature Name	Reason	Test Performed
1	Date	Dropped this column since we've created a replacement for this column named 'days left'	NA
2	Flight	Dropped this column since it has high cardinality making it similar to IDs type of data.	NA
3	From	Dropped because of low feature importance in all observations.	Lasso, DecisionTreeRegressor, RandomForestRegressor
4	Destination	Dropped because of low feature importance in all observations.	Lasso, DecisionTreeRegressor, RandomForestRegressor
5	Departure time	Dropped because of low feature importance in all observations.	Lasso, DecisionTreeRegressor, RandomForestRegressor
6	Arrival time	Dropped because of low feature importance in all observations.	Lasso, DecisionTreeRegressor, RandomForestRegressor

Stage 3: Model Building:

S No	Type of Problem	Approach	Algorithm Name
1	Regression	Distance-Based	KNeighborsRegressor
2	Regression	Decision Tree	DecisionTreeRegressor
3	Regression	Linear Model	LinearRegression
4	Regression	Robust Linear Model	RANSACRegressor
5	Regression	Robust Linear Model	TheilSenRegressor
6	Regression	Robust Linear Model	HuberRegressor
7	Regression	Linear Model with Regularization	Lasso
8	Regression	Linear Model with Regularization	Ridge
9	Regression	Linear Model with Regularization	ElasticNet
10	Regression	Ensemble - Bagging	RandomForestRegressor
11	Regression	Ensemble - Boosting	GradientBoostingRegressor
12	Regression	Ensemble - Boosting	XGBRegressor
13	Regression	Ensemble - Boosting	AdaBoostRegressor

1. **KNeighbors Regressor:** K-nearest neighbors (KNN) regression predicts the target variable by averaging the values of its k-nearest neighbors in the feature space. It assumes that similar data points have similar target values, making it suitable for locally smooth relationships between features and the target.
2. **Decision Tree Regressor:** Decision tree regression builds a model that predicts the target variable by partitioning the data into subsets based on the values of input features. It recursively splits the data based on feature thresholds, aiming to minimize the variance of the target variable within each subset.
3. **Linear Regression:** Linear regression models the relationship between the dependent variable and one or more independent variables by fitting a linear equation. It assumes a linear relationship between the variables and is widely used for predicting continuous outcomes.
4. **RANSAC Regressor:** RANSAC (RANdom SAmple Consensus) regression fits a regression model to a subset of data points (inliers) while ignoring outliers. It iteratively refits the model to improve accuracy by minimizing the impact of outliers on the model coefficients.

5. **Theil-Sen Regressor:** Theil-Sen regression estimates the slope of the relationship between variables using the median of slopes between all pairs of sample points. It is robust to outliers and works well in the presence of noise and heteroscedasticity (unequal variance across data).
6. **Huber Regressor:** Huber regression combines the best properties of least squares and least absolute deviation methods. It minimizes the sum of squared errors for samples close to the regression line (like least squares) and absolute error for samples far from it (like least absolute deviation).
7. **Lasso Regression:** Lasso (Least Absolute Shrinkage and Selection Operator) regression adds a penalty to the sum of absolute values of the regression coefficients, promoting sparsity and feature selection by shrinking some coefficients to zero.
8. **Ridge Regression:** Ridge regression adds a penalty to the sum of squared coefficients (L2 regularization), reducing the effect of multicollinearity and shrinking the coefficients towards zero, but rarely to zero.
9. **ElasticNet Regression:** ElasticNet regression combines penalties from both Lasso and Ridge, using a convex combination of L1 and L2 regularization terms. It balances between feature selection (like Lasso) and handling multicollinearity (like Ridge).
10. **Random Forest Regressor:** Random forest builds multiple decision trees during training and outputs the average prediction of the individual trees. It reduces overfitting compared to a single decision tree and provides high accuracy.
11. **Gradient Boosting Regressor:** Gradient boosting builds an ensemble of trees sequentially, where each tree corrects the errors of the previous one. It combines the predictions of multiple weak learners (decision trees) to produce a strong prediction model.
12. **XGBoost Regressor:** XGBoost (Extreme Gradient Boosting) is an optimized distributed gradient boosting library designed for efficient computation. It improves upon traditional gradient boosting with system optimizations and algorithmic enhancements.
13. **AdaBoost Regressor:** AdaBoost (Adaptive Boosting) combines multiple weak learners (typically decision trees) to create a strong predictor. It assigns higher weights to incorrectly predicted instances, focusing subsequent learners on harder cases.

Stage 4: Model Training:

Basic Models:

Model	Train MAE	Train MSE	Train RMSE	Train R2	Train Adj R2	Test MAE	Test MSE	Test RMSE	Test R2	Test Adj R2
KNeighbours	2791.82	2.28 E+07	4777.5	0.96	0.96	3427.56	3.49 E+07	5904.78	0.93	0.93
DecisionTree	1033.68	7.52 E+06	2743.07	0.99	0.99	3874.28	4.92 E+07	7013.73	0.91	0.91
LinearRegression	4592.36	4.84 E+07	6957.66	0.91	0.91	4594.61	4.94 E+07	7030.13	0.91	0.91
RANSAC	4544.57	6.18 E+07	7861.98	0.88	0.88	4561.98	6.27 E+07	7916.18	0.88	0.88
TheilSen	4477.81	4.91 E+07	7005.85	0.9	0.9	4491.58	5.02 E+07	7084.13	0.9	0.9
HuberRegressor	4270.72	5.15 E+07	7173.77	0.9	0.9	4288.27	5.27 E+07	7259.65	0.9	0.9
Lasso	4593.04	4.84 E+07	6957.96	0.91	0.91	4596.02	4.94 E+07	7030.97	0.91	0.91
Ridge	4593.41	4.84 E+07	6957.65	0.91	0.91	4595.61	4.94 E+07	7030.34	0.91	0.91
Elastic Net	10524.03	1.73 E+08	13140.6	0.66	0.66	10685.08	1.78 E+08	13353	0.66	0.66
RandomForest	1679.38	9.89 E+06	3144.75	0.98	0.98	3341.12	3.49 E+07	5906.82	0.93	0.93
GradientBoosting	3175.06	2.91 E+07	5393.16	0.94	0.94	3196	2.95 E+07	5434.52	0.94	0.94
XGBoost	2779.56	2.25 E+07	4742.14	0.96	0.96	3059.9	2.80 E+07	5294.74	0.95	0.95
AdaBoost	3726.34	3.48 E+07	5901.17	0.93	0.93	3737.32	3.54 E+07	5946.64	0.93	0.93

- From above we can observe that Elastic Net has quite the poor performance of all the models and XGBoost has the best overall R2 scores on both train and test data.

Hyper-Parameter Tuning Using RandomizedSearchCV:

S No	Algorithm Name	Hyper-parameter tuning	Metric used for Evaluation
1	KNN	n_neighbors: 2-30, weights: uniform, distance	Mean Squared Error (MSE), R-squared, MAE, RMSE, ADJ_R2
2	Decision Tree	max_depth: 1-45 (step 5)	Mean Squared Error (MSE), R-squared, MAE, RMSE, ADJ_R2
3	Linear Regression	None	Mean Squared Error (MSE), R-squared, MAE, RMSE, ADJ_R2
4	RANSAC Regression	None	Mean Squared Error (MSE), R-squared, MAE, RMSE, ADJ_R2
5	TheilSen Regression	None	Mean Squared Error (MSE), R-squared, MAE, RMSE, ADJ_R2
6	Huber Regression	None	Mean Squared Error (MSE), R-squared, MAE, RMSE, ADJ_R2
7	Lasso Regression	alpha: 0.01, 0.1, 1, 10, 100	Mean Squared Error (MSE), R-squared, MAE, RMSE, ADJ_R2
8	Ridge Regression	alpha: 0.01, 0.1, 1, 10, 100	Mean Squared Error (MSE), R-squared, MAE, RMSE, ADJ_R2
9	Random Forest	n_estimators: 50-199, max_depth: None, 10, 20, 30, 40, 50	Mean Squared Error (MSE), R-squared, MAE, RMSE, ADJ_R2
10	Gradient Boosting	n_estimators: 50-199, max_depth: 3, 4, 5, 6, None	Mean Squared Error (MSE), R-squared, MAE, RMSE, ADJ_R2
11	XGBoost	n_estimators: 50-199, max_depth: 3, 4, 5, 6, 8, 10, learning_rate: 0.01, 0.1, 0.15, 0.3	Mean Squared Error (MSE), R-squared, MAE, RMSE, ADJ_R2
12	AdaBoost	n_estimators: 50-199, learning_rate: 0.01, 0.1, 0.15, 0.3	Mean Squared Error (MSE), R-squared, MAE, RMSE, ADJ_R2

Stage 5: Model Evaluation:

S No	Model	Training Time	Testing Time	R2 Score	Adj R2 Score	Hyperparameter
1	KNeighbours	0.07761	1.048659	0.94	0.94	n_neighbors=29
2	DecisionTree	0.072904	0.004241	0.94	0.94	max_depth=11
3	LinearRegression	0.01687	0.004502	0.91	0.91	None
4	RANSAC	0.321958	0.002916	0.87	0.87	None
5	TheilSen	12.76159	0.004496	0.90	0.90	None
6	HuberRegressor	0.501576	0.002852	0.90	0.90	None
7	Lasso	0.033868	0.002928	0.91	0.91	alpha=0.01
8	Ridge	0.00771	0.002706	0.91	0.91	alpha=0.1
9	RandomForest	3.781979	0.123334	0.95	0.95	max_depth=10, n_estimators=79
10	GradientBoosting	8.884084	0.071349	0.95	0.95	max_depth=6, n_estimators=160
11	XGBoost	0.24346	0.021409	0.95	0.95	max_depth=5, n_estimators=74, learning_rate=0.3
12	AdaBoost	3.170216	0.094205	0.93	0.93	learning_rate=0.1, n_estimators=79

<u>From the above table, here are a few observations:</u>

- RandomForest, GradientBoosting, and XGBoost models achieve the highest R2 and Adjusted R2 Scores of 0.95.
- The TheilSen model has an exceptionally high training time (12.761589 seconds), significantly longer than any other model.
- The KNeighbours model has the highest testing time (1.048659 seconds), which is much longer compared to other models.
- Ridge has the shortest training time (0.007710 seconds) and very short testing time (0.002706 seconds).

- XGBoost balances well with a relatively short training time (0.243460 seconds) and testing time (0.021409 seconds).
- LinearRegression, Ridge, and Lasso models all have identical R2 and Adjusted R2 Scores of 0.91, indicating similar predictive performance.

Stage 6: Model Deployment:

The flight ticket price prediction model has been deployed via a Streamlit web application on a local server environment. This deployment aims to provide users with a convenient interface for predicting flight ticket prices based on various parameters.

Deployment Environment:

The Streamlit app is hosted on a local machine with Python and necessary libraries installed to support the application's functionality.

Deployment Steps:

1. Environment Setup:
    - Installed required Python packages including Streamlit for web application development.
2. Application Development:
    - Developed the Streamlit web application using Python, incorporating the flight ticket price prediction model.
3. Testing and Validation:
    - Conducted testing to ensure the app functions correctly, handling various inputs and scenarios effectively.

Functionality:

The deployed app enables users to input flight details such as airline, class, date, and other relevant parameters. It then provides an estimated price for the flight based on historical data and machine learning predictions.

Usage Instructions:

1. Input Details:
    - Users can enter details such as departure city, destination, departure date, number of passengers, etc.
2. Prediction Output:
    - Upon submitting the details, the app calculates and displays the predicted flight ticket price using the deployed machine learning model.

Future Considerations:

Future enhancements may involve:

- Exploring deployment options on cloud servers for broader accessibility.
- Adding features like real-time updates, multi-city travel predictions, and user feedback mechanisms to improve the application's utility and user experience.

Challenges Faced:

- While cleaning the dataset, some tags which we're causing problems for changing the wrong data type to correct like "stops" and "time taken".
- Also, while dealing with the datetime format columns.
- While doing the hyper-parameter tuning and selections of parameters.

Conclusion:

The best models are the following:

- Decision Tree can be considered the best model with quite the fast prediction time (0.004241 seconds) and with a slight trade-off in the R2 Score (0.94).
- XGBoost has the best overall performance due to its perfect balance of high R2 Score (0.95) and a bit slow prediction time (0.071349 seconds).

Thus, Decision Tree can be considered the best choice for scenarios where computational efficiency is prioritized and a slight reduction in predictive performance (from 0.95 to 0.94) is acceptable.