M1-FA2.1: Chapter Project (Data Exploration and Summary)

In this project, the researchers were tasked to explore and summarize airline flights using any appropriate algorithm that could predict airline price based on selected variables. Attributes such as *Airline*, *Source*, *Destination*, *Time of Departure and Arrival*, and *Date of Journey* were taken into consideration as to how they might affect the dependent variable *Price*. The results of the relationship between the independent and dependent variables were expressed through visualizations in RStudio.

I. Installing Packages and Dependencies

To prepare the RStudio environment for the codes that will be run, the following packages and their dependencies were initially installed and unpacked.

```
install.packages("ggplot2")
install.packages("dplyr")
install.packages("psych")
install.packages("caret")
install.packages("tseries")
install.packages("forecast")
```

```
library(ggplot2)
library(dplyr)
library(psych)
library(caret)
library(tseries)
library(forecast)
```

As seen in the figure above, the *ggplot2* and *dplyr* packages from the previous chapter project were installed. These were the same packages used in the Regression Model chapter project for data visualizations and data manipulation. The new packages (i.e. *caret*, *tseries*, and *forecast*) that will be used in this assignment will later help implement the time series analysis model that will predict the airline price based on a specified variable. After the packages and libraries have finished installing, the console should look like the figure below.

```
Attaching package: 'dplyr'

The following objects are masked from 'package:stats':

    filter, lag

The following objects are masked from 'package:base':

    intersect, setdiff,
    setequal, union

> library(psych)

Attaching package: 'psych'

The following objects are masked from 'package:ggplot2':

    %+%, alpha

> library(caret)
Loading required package: lattice
> library(tseries)
Registered S3 method overwritten by 'quantmod':
  method            from
  as.zoo.data.frame zoo

    'tseries' version:
    0.10-53

    'tseries' is a package
    for time series analysis
    and computational
    finance.

    See
    'library(help="tseries")'
    for details.

> library(forecast)
This is forecast 8.21
  Need help getting started? Try the online textbook FPP:
  http://otexts.com/fpp2/
```

Then, to set a proper working directory for the program and its referenced file, the code snippet below was run.

```
# Set a working directory to store all the related datasets and files
setwd("C:/Users/Anton/Documents/3Q2223/CS174/Module 1/M1-FA2.1 Chapter Project (Data Exploration and Summary)")
```

Within the specified working directory, there exists the dataset that will be used in this project. Using the *read.csv()* function, the dataset was imported to the data frame variable *flights.df*.

```
# Import the Data_Train.csv dataset using the read.csv() function
flights.df <- read.csv("Data_Train.csv", stringsAsFactors = TRUE)
```

II. Data Preparation

Before the data is explored to identify its correlations, the data was cleaned and prepared through format conversion, irrelevant and redundant data removal, and missing data identification. Since the dataset contained date values, those were converted to the appropriate date format using the **as.Date() function**.

```
> flights.df$Date_of_Journey = as.Date(flights.df$Date_of_Journey, "%d/%m/%y
")
```

Then, to remove any redundant data and columns, the **subset() function** was run. The code snippet below shows the line of code that was run to remove the redundant data. One specific attribute was also set to NULL as its column did not contain any information that will help in fulfilling the objective of the assignment.

```
> flights.df = subset(flights.df, Airline != "Trujet" & Airline != "Vistara
Premium economy" & Airline != "Jet Airways Business" & Airline != "Multiple
carriers Premium economy")

> flights.df$Route <- NULL
```

To confirm that the data has had its specified values set to NULL, the table() function was run to reveal the following output.

```
> table(flights.df$Airline)

                   Air Asia                  Air India                      GoAir                     IndiGo                  Jet Airways
                        319                       1752                        194                       2053                       3849
          Jet Airways Business  Multiple carriers Multiple carriers Premium economy                  SpiceJet                     Trujet
                          0                       1196                          0                        818                          0
                    Vistara  Vistara Premium economy
                        479                          0
```

Lastly, to identify if there are any missing values, the **colSums() function** was run. The figure below shows that the specified attributes do not have missing values.

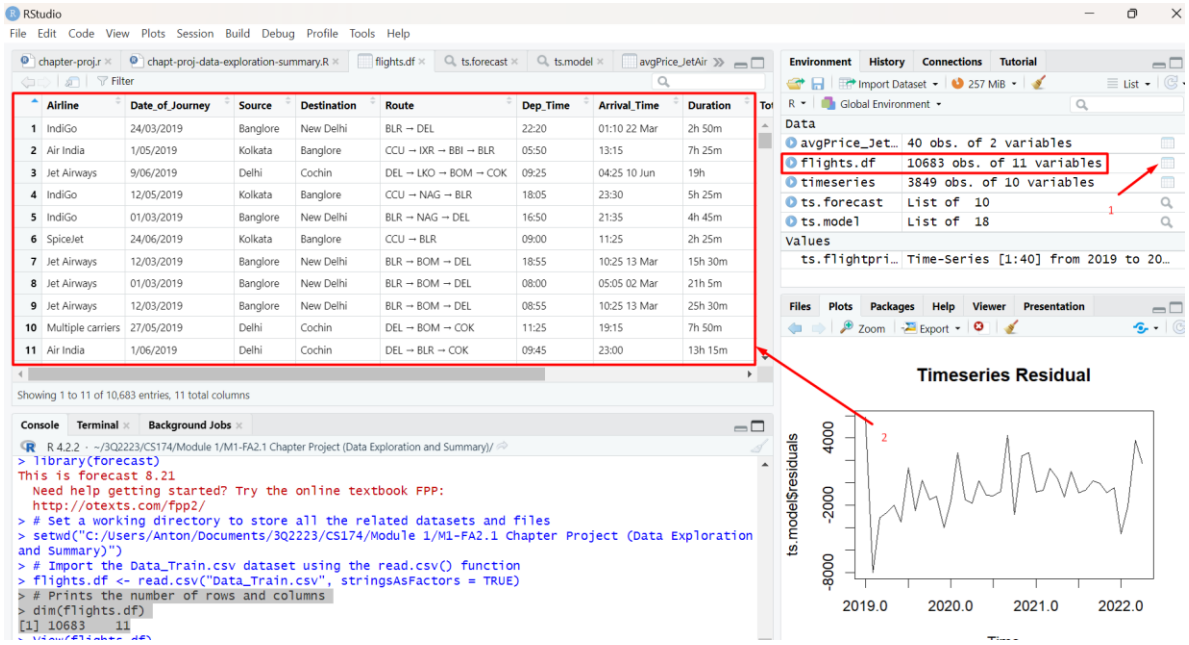
```
> # Identify missing values
> colSums(is.na(flights.df))
        Airline  Date_of_Journey           Source      Destination        Dep_Time    Arrival_Time
              0                0                0                0                0               0
       Duration     Total_Stops Additional_Info            Price
              0                0                0                0
```

III. Data Exploration and Summary

After the dataset had been imported and cleaned, the data was explored through manipulation, sorting, and printing specified values of the table onto the console. The first function that was used to explore the data was the **dim() function**, which displays the number of rows and columns of its parameter. Its output should look like the code snippet below.

```
> # Prints the number of rows and columns
> dim(flights.df)
[1] 10683    11
```

The function's output states that the dataset has **10,683 entries with 11 variables**. The *flights.df* data frame can also be viewed in RStudio on the Source column.



The next function used was the **head() function**. This function will print the first few lines of data on the console, allowing the members of the group to see the attribute names that they will use during further manipulating of the data.

```
> View(flights.df)
> # Prints the first few lines of the data on the console
> print(head(flights.df))
      Airline Date_of_Journey    Source Destination                  Route Dep_Time Arrival_Time
1      IndiGo      24/03/2019 Banglore   New Delhi              BLR → DEL    22:20 01:10 22 Mar
2   Air India       1/05/2019  Kolkata    Banglore CCU → IXR → BBI → BLR    05:50         13:15
3 Jet Airways       9/06/2019    Delhi      Cochin DEL → LKO → BOM → COK    09:25 04:25 10 Jun
4      IndiGo      12/05/2019  Kolkata    Banglore        CCU → NAG → BLR    18:05         23:30
5      IndiGo      01/03/2019 Banglore   New Delhi        BLR → NAG → DEL    16:50         21:35
6    SpiceJet      24/06/2019  Kolkata    Banglore              CCU → BLR    09:00         11:25
  Duration Total_Stops Additional_Info Price
1   2h 50m    non-stop         No info  3897
2   7h 25m     2 stops         No info  7662
3      19h     2 stops         No info 13882
4   5h 25m      1 stop         No info  6218
5   4h 45m      1 stop         No info 13302
6   2h 25m    non-stop         No info  3873
>
```

Since the main objective of the assignment is to understand which variables affect the airline price, the data was sorted in ascending order in terms of the attribute *Price* to see what kind of relationship the dependent variable has with the other variables. To sort the flights, the **order() function** was used to sort the data from the flight of the lowest cost to that of the highest cost.

	Airline	Date_of_Journey	Source	Destination	Route	Dep_Time	Arrival_Time	Duration	Total_Stops	Additional_Info	Price
4067	SpiceJet	21/03/2019	Mumbai	Hyderabad	BOM → HYD	22:45	00:10 22 Mar	1h 25m	non-stop	No info	1759
4275	SpiceJet	27/03/2019	Mumbai	Hyderabad	BOM → HYD	22:45	00:10 28 Mar	1h 25m	non-stop	No info	1759
4840	SpiceJet	3/04/2019	Mumbai	Hyderabad	BOM → HYD	22:45	00:15 02 Apr	1h 30m	non-stop	No info	1759
10514	SpiceJet	27/03/2019	Mumbai	Hyderabad	BOM → HYD	05:45	07:05	1h 20m	non-stop	No info	1759
1514	Jet Airways	27/03/2019	Mumbai	Hyderabad	BOM → HYD	02:55	04:25	1h 30m	non-stop	In-flight meal not included	1840
229	SpiceJet	21/05/2019	Mumbai	Hyderabad	BOM → HYD	05:45	07:15	1h 30m	non-stop	No check-in baggage included	1965
388	SpiceJet	18/06/2019	Mumbai	Hyderabad	BOM → HYD	13:15	14:45	1h 30m	non-stop	No check-in baggage included	1965
656	SpiceJet	3/05/2019	Mumbai	Hyderabad	BOM → HYD	13:15	14:45	1h 30m	non-stop	No check-in baggage included	1965
1473	SpiceJet	21/05/2019	Mumbai	Hyderabad	BOM → HYD	13:15	14:45	1h 30m	non-stop	No check-in baggage included	1965
1581	SpiceJet	24/06/2019	Mumbai	Hyderabad	BOM → HYD	22:45	00:15 25 Jun	1h 30m	non-stop	No check-in baggage included	1965
1653	SpiceJet	9/05/2019	Mumbai	Hyderabad	BOM → HYD	05:45	07:15	1h 30m	non-stop	No check-in baggage included	1965
1719	SpiceJet	24/05/2019	Mumbai	Hyderabad	BOM → HYD	05:45	07:15	1h 30m	non-stop	No check-in baggage included	1965
1993	SpiceJet	6/06/2019	Mumbai	Hyderabad	BOM → HYD	22:45	00:15 07 Jun	1h 30m	non-stop	No check-in baggage included	1965
2103	SpiceJet	27/06/2019	Mumbai	Hyderabad	BOM → HYD	13:15	14:45	1h 30m	non-stop	No check-in baggage included	1965
2416	SpiceJet	18/05/2019	Mumbai	Hyderabad	BOM → HYD	22:45	00:15 19 May	1h 30m	non-stop	No check-in baggage included	1965
2427	SpiceJet	18/03/2019	Mumbai	Hyderabad	BOM → HYD	22:45	00:10 19 Mar	1h 25m	non-stop	No check-in baggage included	1965
2725	SpiceJet	21/05/2019	Mumbai	Hyderabad	BOM → HYD	22:45	00:15 22 May	1h 30m	non-stop	No check-in baggage included	1965
3506	SpiceJet	15/05/2019	Mumbai	Hyderabad	BOM → HYD	22:45	00:15 16 May	1h 30m	non-stop	No check-in baggage included	1965
3578	SpiceJet	1/04/2019	Mumbai	Hyderabad	BOM → HYD	13:15	14:45	1h 30m	non-stop	No check-in baggage included	1965
3726	SpiceJet	27/05/2019	Mumbai	Hyderabad	BOM → HYD	22:45	00:15 28 May	1h 30m	non-stop	No check-in baggage included	1965
4535	SpiceJet	3/06/2019	Mumbai	Hyderabad	BOM → HYD	13:15	14:45	1h 30m	non-stop	No check-in baggage included	1965
4596	SpiceJet	3/05/2019	Mumbai	Hyderabad	BOM → HYD	05:45	07:15	1h 30m	non-stop	No check-in baggage included	1965
5328	SpiceJet	3/04/2019	Mumbai	Hyderabad	BOM → HYD	05:45	07:15	1h 30m	non-stop	No check-in baggage included	1965
5743	SpiceJet	6/05/2019	Mumbai	Hyderabad	BOM → HYD	05:45	07:15	1h 30m	non-stop	No check-in baggage included	1965
5789	SpiceJet	9/05/2019	Mumbai	Hyderabad	BOM → HYD	22:45	00:15 10 May	1h 30m	non-stop	No check-in baggage included	1965
5941	SpiceJet	6/06/2019	Mumbai	Hyderabad	BOM → HYD	13:15	14:45	1h 30m	non-stop	No check-in baggage included	1965
6143	SpiceJet	15/06/2019	Mumbai	Hyderabad	BOM → HYD	13:15	14:45	1h 30m	non-stop	No check-in baggage included	1965
6688	SpiceJet	3/04/2019	Mumbai	Hyderabad	BOM → HYD	13:15	14:45	1h 30m	non-stop	No check-in baggage included	1965
7201	SpiceJet	1/05/2019	Mumbai	Hyderabad	BOM → HYD	22:45	00:15 02 May	1h 30m	non-stop	No check-in baggage included	1965
7293	SpiceJet	12/05/2019	Mumbai	Hyderabad	BOM → HYD	05:45	07:15	1h 30m	non-stop	No check-in baggage included	1965

Showing 1 to 31 of 10,683 entries, 11 total columns

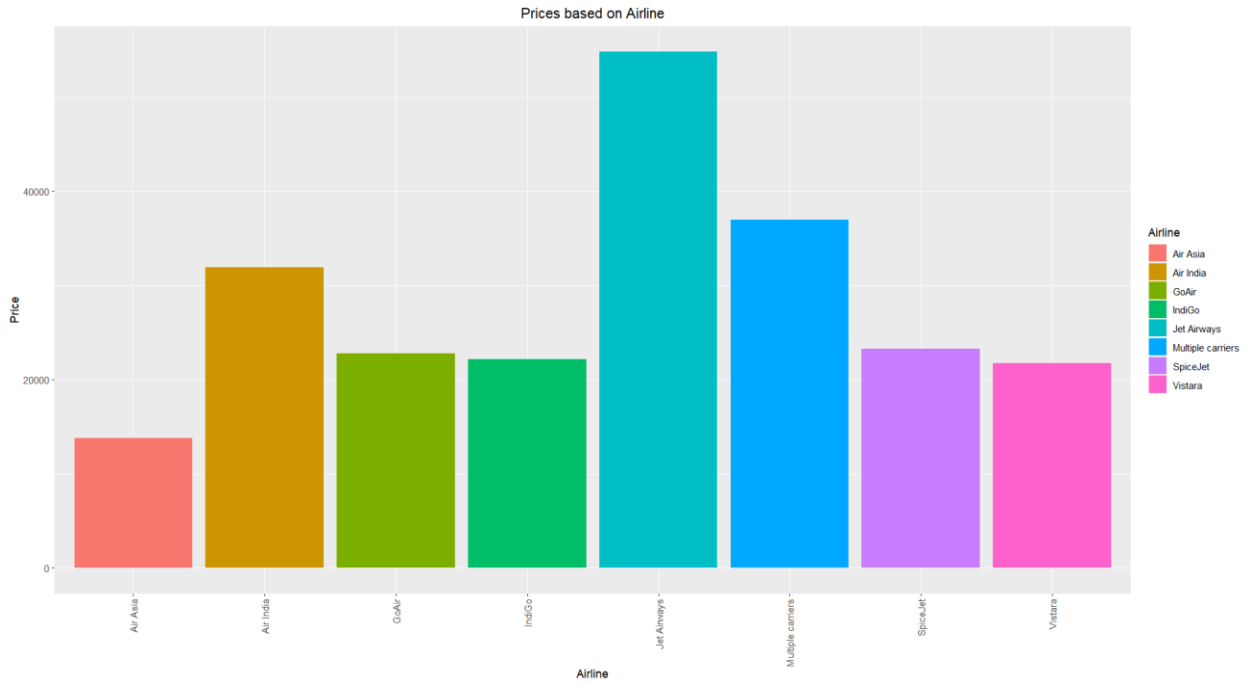
As seen in the figure of the data frame above, the dataset has been reorganized according to price. Although the dataset is too saturated to be fully comprehended by the naked eye, one can immediately recognize a correlation between the price, airline, source, and destination. Unfortunately, looking at the dataset alone is not enough nor practical to understand the data. To enable a more comprehensive approach, the succeeding section will portray these relationships using data visualizations.

The figure below shows a summary of the *flights.df* data frame.

```
> summary(flights.df)
              Airline     Date_of_Journey          Source        Destination      Dep_Time
 Jet Airways      :3849   Min.   :2020-03-01   Banglore:2191   Banglore :2871   18:55  : 233
 IndiGo           :2053   1st Qu.:2020-03-27   Chennai : 380   Cochin   :4522   17:00  : 227
 Air India        :1752   Median :2020-05-15   Delhi   :4522   Delhi    :1264   07:05  : 204
 Multiple carriers:1196   Mean   :2020-05-04   Kolkata :2871   Hyderabad: 696   10:00  : 203
 SpiceJet         : 818   3rd Qu.:2020-06-06   Mumbai  : 696   Kolkata  : 380   07:10  : 202
 Vistara          : 479   Max.   :2020-06-27                   New Delhi: 927   20:00  : 185
 (Other)          : 513                                                         (Other):9406
  Arrival_Time     Duration      Total_Stops                 Additional_Info
 19:00  : 423   2h 50m : 549          :   1   No info                      :8325
 21:00  : 357   1h 30m : 386   1 stop  :5607   In-flight meal not included :1982
 19:15  : 331   2h 45m : 337   2 stops :1518   No check-in baggage included: 320
 16:10  : 154   2h 55m : 337   3 stops :  45   1 Long layover              :  19
 12:35  : 121   2h 35m : 328   4 stops :   1   Change airports             :   7
 20:45  : 112   3h     : 261   non-stop:3488   No Info                     :   3
 (Other):9162   (Other):8462                   (Other)                     :   4
     Price
 Min.   : 1759
 1st Qu.: 5267
 Median : 8372
 Mean   : 9057
 3rd Qu.:12373
 Max.   :54826
```

IV. Data Visualizations and Analysis

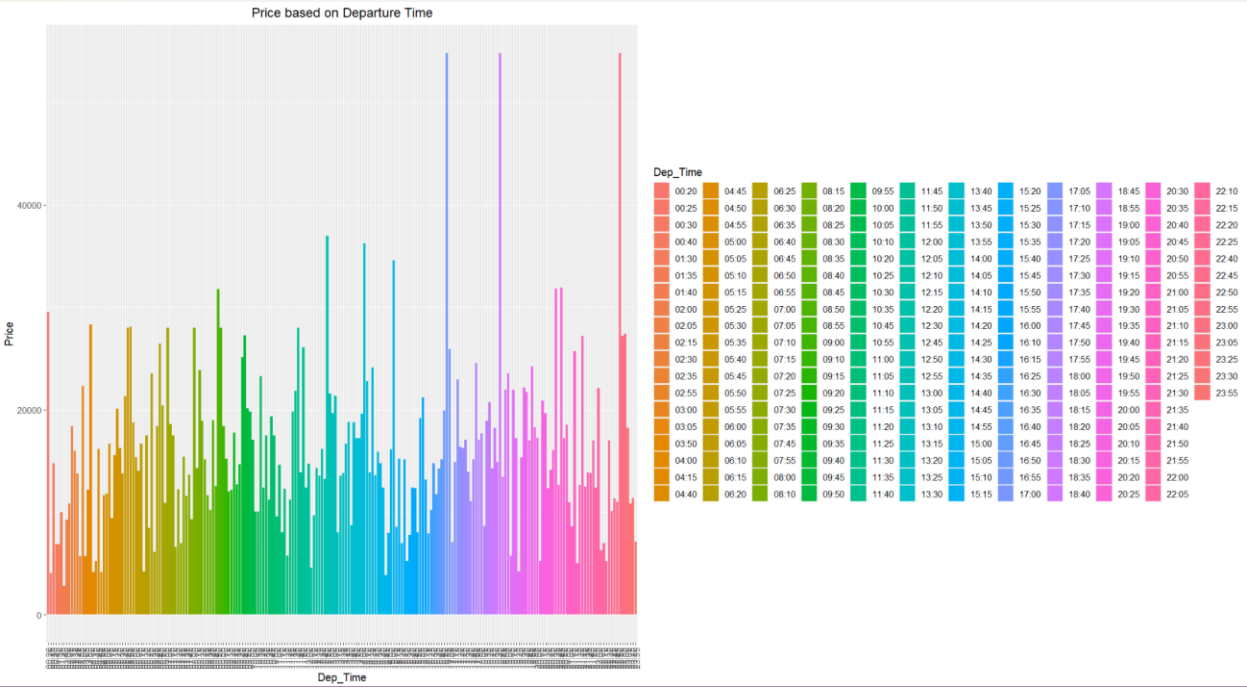
As mentioned in the previous section, correlations between the price and the airline, source, and destination were recognized by simply looking at the sorted dataset. The first correlation that was identified was the one between *Price* and *Airline*, whose relationship can be better understood through the figure below.



Price based on Airline

According to the *Prices based on Airline* bar graph, the Jet Airways airline has the highest flight cost with a price of nearly six thousand. On the other hand, the airline with the least flight cost is *Air Asia* with a price of less than two thousand. Since Jet Airways airline has the highest cost in flight tickets, its price data will be extracted to be grouped using the **group_by() function** with the *Date_of_Journey* attribute to derive the average price of Jet Airways. The *Date_of_Journey* attribute will be set as the independent variable that will affect the dependent variable *Price* because it is the only other numerical variable available in the dataset that could be compared with the cost of the flight tickets. (The results of the correlation and forecast will be further discussed in the Time Series Analysis section.)

Other correlations were explored, as evidenced by the figures below, but were too saturated and unrelated to *Price*. Furthermore, attributes *Dep_Time* and *Arrival_Time* would be unreliable variables to consider given that any delays in flight schedule does not alter nor affect the price of a flight.



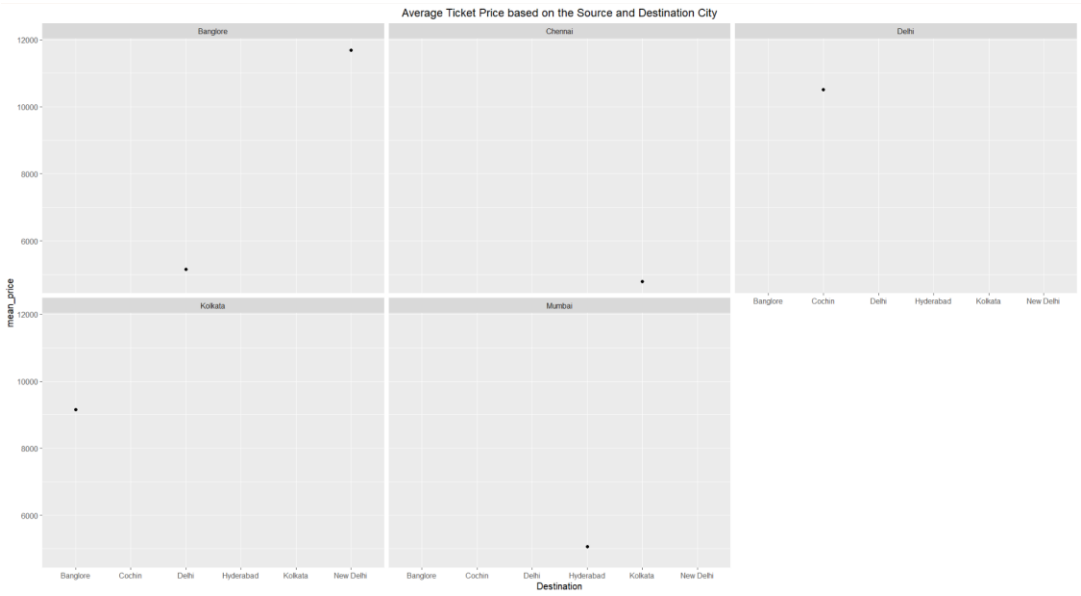
Price based on Departure Time

Price based on Arrival Time

Another correlation observed was that between *Price* and *Source* and *Destination*. To understand the relationship between these values, the **mean_price** in terms of *Source* and *Destination* was calculated. According to the table below, flights from Banglore to New Delhi usually cost more, followed by flights from Delhi to Cochin.

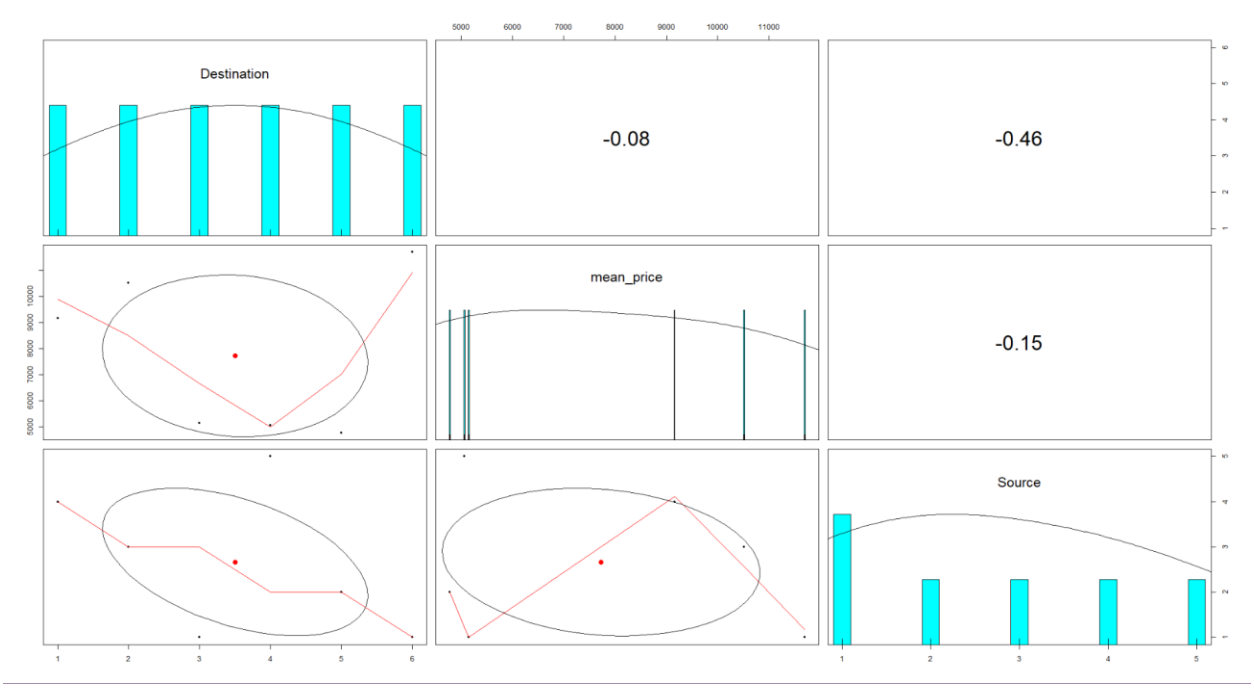
	Source	Destination	mean_price
1	Banglore	Delhi	5143.266
2	Banglore	New Delhi	11698.104
3	Chennai	Kolkata	4778.484
4	Delhi	Cochin	10519.729
5	Kolkata	Banglore	9158.389
6	Mumbai	Hyderabad	5061.030

price_comp



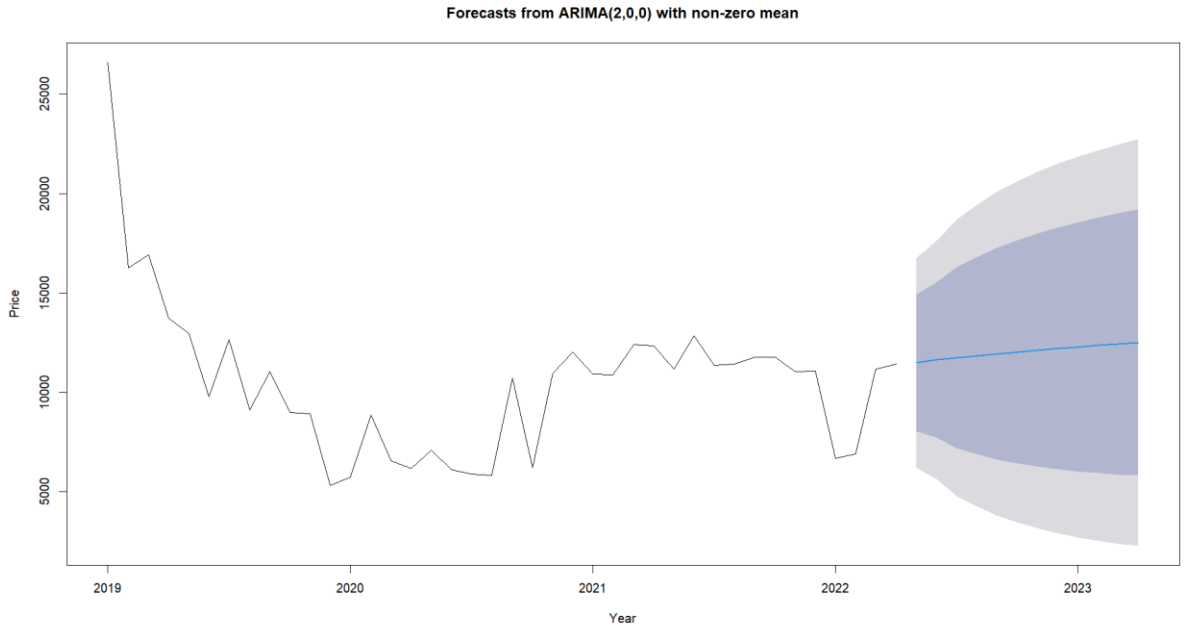
Average Ticket Price based on the Source and Destination City

The correlation between the Destination, mean_price, and Source can also be further understood by referring to the figure below.



Correlation between Destination, mean_price, and Source

V. Airline Price Prediction using Auto Arima Timeseries



We used time series using AUTO ARIMA to forecast the airline price for Jet Airways in 2023. We chose Jet Airways because it had the highest prices among other airlines. The above graph plot estimated forecasted values of airline price if it continues to be widespread this year. Based on the code snippet below, we predicted that the airline ticket price would be 12,502.64 in April 2023.

```
Forecasts:
         Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
May 2022       11494.35 8042.651 14946.05 6215.433 16773.27
Jun 2022       11633.27 7723.252 15543.28 5653.415 17613.12
Jul 2022       11736.89 7191.049 16282.74 4784.624 18689.16
Aug 2022       11846.02 6900.503 16791.54 4282.504 19409.54
Sep 2022       11944.36 6632.871 17255.85 3821.140 20067.58
Oct 2022       12039.09 6434.783 17643.40 3468.041 20610.15
Nov 2022       12127.72 6270.007 17985.43 3169.122 21086.32
Dec 2022       12211.69 6138.963 18284.42 2924.254 21499.13
Jan 2023       12290.82 6032.070 18549.56 2718.890 21862.74
Feb 2023       12365.55 5945.893 18785.22 2547.529 22183.58
Mar 2023       12436.07 5876.284 18995.86 2403.743 22468.40
Apr 2023       12502.64 5820.533 19184.74 2283.240 22722.04
```

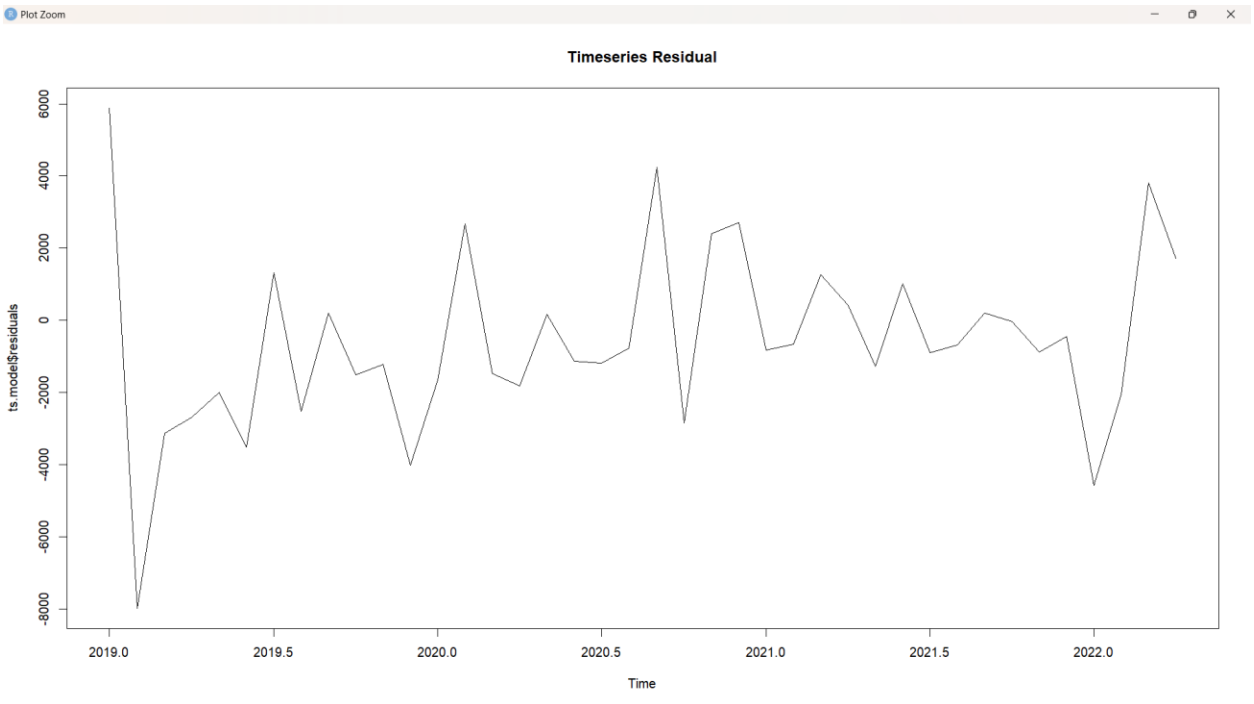
Next, we needed to ensure that our model is stationary, meaning it does not depend on time or trends. A stationary time series is required for better prediction of the airline price. To achieve this goal, we used Augmented Dickey-Fuller (ADF) to identify whether the time series is stationary. Based on the results below, our time series is stationary and expected since we have used AUTO ARIMA for our time series.

```
> #Hypothesis Testing using ADF
> adf.test(ts.forecast$fitted, alternative = "stationary")

        Augmented Dickey-Fuller Test

data:  ts.forecast$fitted
Dickey-Fuller = -2.9616, Lag order = 3, p-value = 0.1961
alternative hypothesis: stationary
```

Finally, we checked to see if the model accurately represented the information in the data. The model's residuals help determine whether our model possesses the fundamental characteristics. As shown in the graph below, the mean of the residuals is almost zero, and the residuals series exhibits no discernible correlation. Except for the one outlier shown in 2019, we can view the residual variance as constant because the residuals' time plot demonstrates that the residuals' variation is mainly constant across the historical data.



References

3.3 Residual Diagnostics | Forecasting: Principles and Practice (2nd Ed). otexts.com/fpp2/residuals.html.

N. (n.d.). *GitHub - notrichbish/airline-ticket-price-prediction: This project covers both Simple Linear Regression and Multiple Linear Regression which are used in prediction airline flight ticket. Moreover, Correlation analysis and Timeseries analysis are performed as well. This project is built as a fulfillment for my masters degree.* GitHub. https://github.com/notrichbish/airline-ticket-price-prediction

Robert Kabacoff - robk@statmethods.net. (n.d.). *Quick-R: Date Values*. https://www.statmethods.net/input/dates.html

Sharda, R., Delen, D., & Turban, E. (2020). *Analytics, Data Science, and Artificial Intelligence: Systems for Decision Support, Global Edition*.

"Why Does a Time Series Have to Be Stationary?" *Cross Validated*, stats.stackexchange.com/questions/19715/why-does-a-time-series-have-to-be-stationary.