

Predict Airline Fares

PERSONAL PROJECT

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Objective & Methodology



Analyze airline fare data to create a predictor for fares in Indian airlines.

Python used to load, clean, and create models.

Models used:
Linear Regression,
Decision Trees,
KNN

RMSE used as
model metric

Summary



Route and additional_info features not used

Route would result in 128 features added in, and additional_info has a lot of missing data.



When comparing Linear Regression, Decision Trees, and KNN, Decision Trees had the smallest root mean squared error.



With outliers removed, decision trees remained the best model, however KNN regression had the best improvement of in terms of RMSE.



In decision trees total_duration was the most importance feature, followed by Journey_day

Raw Data

- Raw data features
 - Airline: string
 - Date_of_Journey: datetime
 - Source
 - Destination
 - Route (removed)
 - Dep_Time/Arrival_Time
 - Duration
 - Total Stops
 - Additional Info (removed)

	Airline	Date_of_Journey	Source	Destination	Route	Dep_Time	Arrival_Time	Duration	Total_Stops	Additional_Info
0	IndiGo	24/03/2019	Banglore	New Delhi	BLR → DEL	22:20	01:10 22 Mar	2h 50m	non-stop	No info
1	Air India	1/05/2019	Kolkata	Banglore	CCU → IXR → BBI → BLR	05:50	13:15	7h 25m	2 stops	No info
2	Jet Airways	9/06/2019	Delhi	Cochin	DEL → LKO → BOM → COK	09:25	04:25 10 Jun	19h	2 stops	No info

Data cleaning & Feature Extraction



Data Cleanup & Feature extraction: Datetime

Step1:

Set Date_of_Journey, Dep_Time, Arrival_Time to datetime to extract features

Step2:

From date_of_journey

- We get Day, Month, and Year

From arrival time and departure time

- We get hour and minute

Journey_Day	Journey_Month	Journey_Year	Dep_Hour	Dep_Min	Arrival_Hour	Arrival_Min
24	3	2019	22	20	1	10
1	5	2019	5	50	13	15



Data Cleanup & Feature extraction: Duration of flight

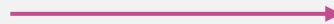
METHOD

- Current format is 2h 30m or 30m as a string.
- Using regex we can replace h with *60, and then do $2*60+30$ and extract that into duration in minutes.

AFTER EXTRACTION

```
df['Duration']
```

0	2h 50m
1	7h 25m
2	19h
3	5h 25m
4	4h 45m
...	...
10678	2h 30m
10679	2h 35m
10680	3h
10681	2h 40m
10682	8h 20m



```
df['Total_Duration_Min']
```

0	170
1	445
2	1140
3	325
4	285
...	...
10678	150
10679	155
10680	180
10681	160
10682	500

Data Cleanup & Feature extraction: total stops

```
df['Total_Stops']
```

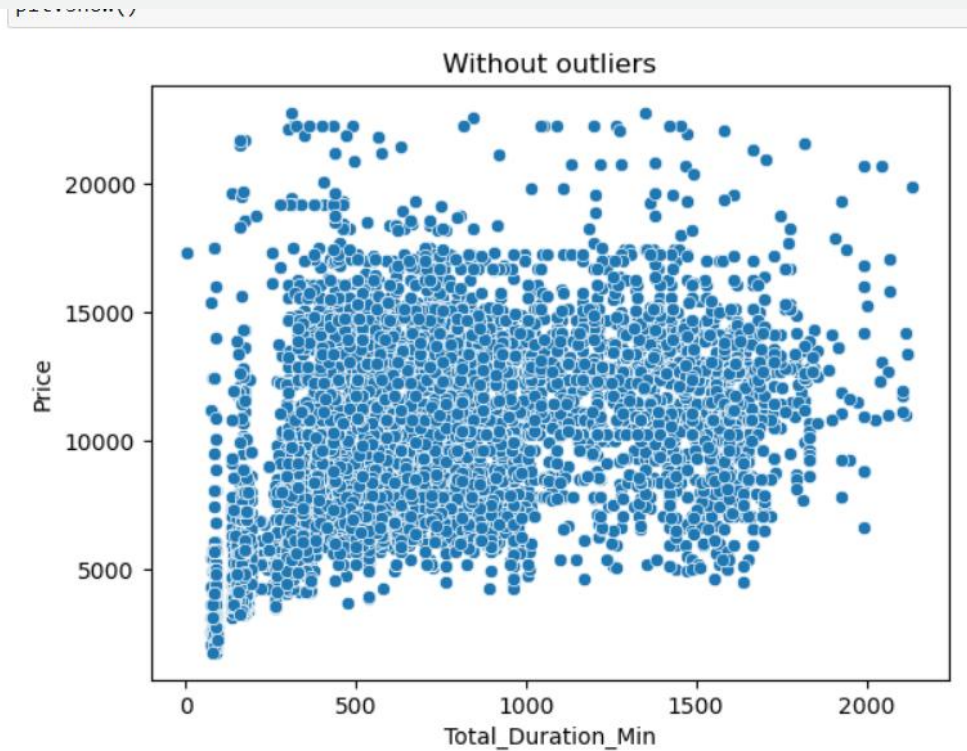
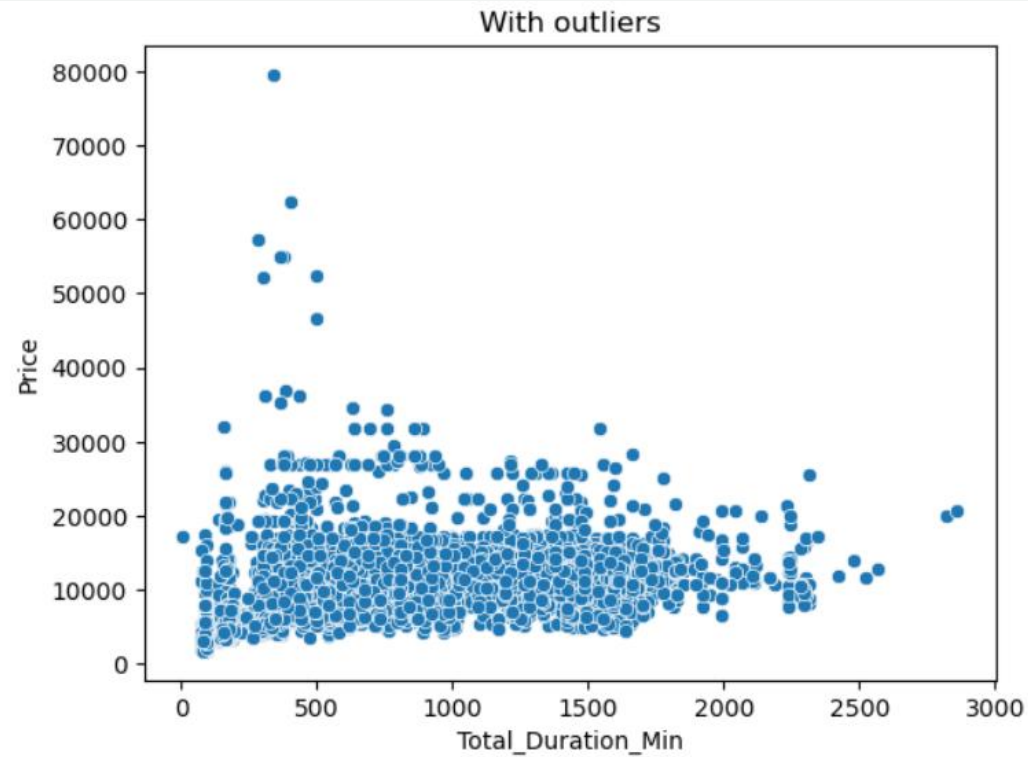
```
] 0      non-stop  
  1      2 stops  
  2      2 stops  
  3      1 stop  
  4      1 stop  
   ...  
10678 non-stop  
10679 non-stop  
10680 non-stop  
10681 non-stop  
10682  2 stops
```

```
df['Total_Stops']
```

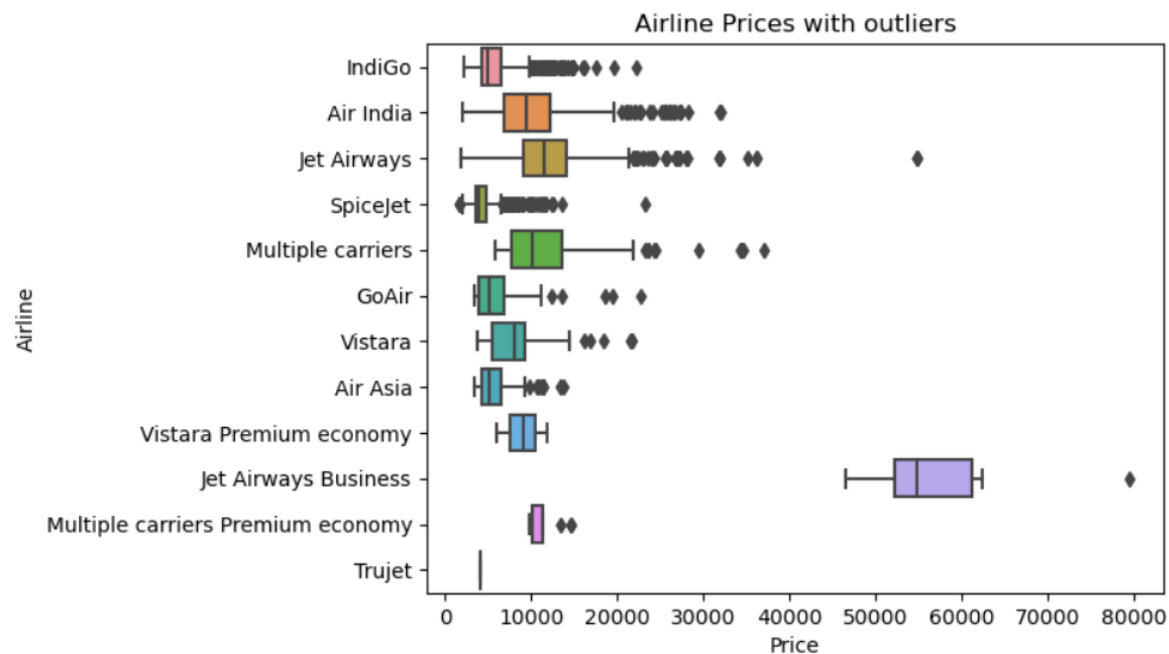
```
: 0      0  
  1      2  
  2      2  
  3      1  
  4      1  
   ..  
10678  0  
10679  0  
10680  0  
10681  0  
10682  2
```



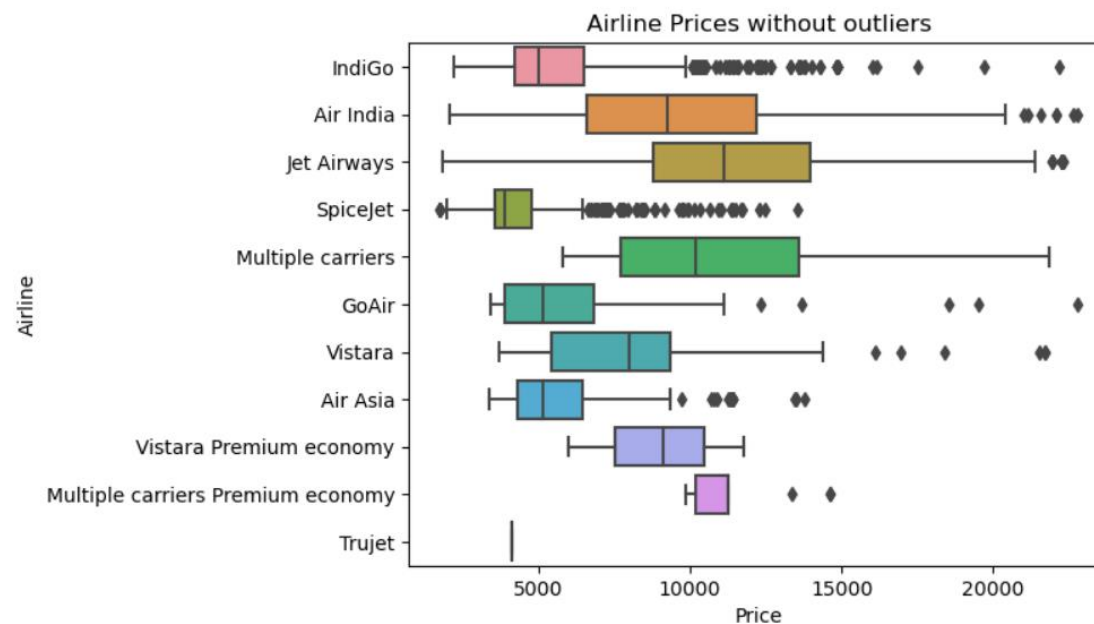
Price vs. Duration



There is a stronger linear relationship when outliers are removed



Most airline prices are similar but Jet Airways Business is a big outlier



Models



Model RMSE comparison with outliers

Linear Regression: 2804.64

Decision Tree: 2539.68

KNN: 3019.20

Based on results, decision tree model is best used for airline fare predictions when comparing the models used.

Future considerations:

Trying deep learning models

RMSE with outliers removed

Linear Regression:
2804.64 ->
2413.24 13.96%
improvement

Regression Tree:
2539.68 ->
2210.22 12.97%
improvement

KNN Regressor:
3019.20 ->
2404.67 20.35%
improvement

