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Identification of centroids of Mohammed V airport arrivals.

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Introduction

The Air Traffic Management (ATM) market is projected to grow from an estimated USD 14.1 billion in 2018 to 18.8 billion by 2025. This growth can be attributed toincreasing airport investments and modernization of ATM infrastructure.

In 2018, Moroccan airports received more than 22,534,000 passengers, according to the National Office of Airports (ONDA) which represents 10 percent more than in 2017. The Agadir airport recorded an increase of 25 percent in passengers; Marrakech 21 percent; Fez 17 percent; Ouarzazate 37 percent; Essaouira 25 percent; and Dakhla 20 percent and even though Mohammed V International Airport in Casablanca has known only an increase by 4 percent from 2017 but it handled 43 percent of Moroccan international air traffic in 2018, receiving 9,732,044 passengers which makes it the busiest airport of Morocco. Increasing air travel has led to an increase in commercial air traffic and since commercial air traffic has been higher and has greater frequency than tactical air traffic. This in turn leads to the increasing need for ATM systems to cope with the increasing commercial air traffic and one of its strategies is aircraft trajectory data by using analysis models.

Models for predicting aircraft motion are an important component of modern aeronautical systems. In this given paper, we developed a method to analyze aircraft's motion and evaluate its efficiency in terminal airspace, the controlled airspace surrounding a given airport. The method fits the model based on a historical dataset of radar-based position measurements of aircraft landings and takeoffs at that airport. We find that the model generates realistic trajectories, provides accurate predictions allowing to control the performance of the system.

This paper presents a characterization of air traffic performance based on aircraft tracking data recorded by surveillance systems. We use unsupervised learning and apply a flight trajectory clustering framework to identify traffic patterns at the terminal for destination Mohammed V International Airport.

Methodology

The data-driven approach for air traffic performance characterization is based on three steps:

First, data is exposed to a data pre-processing which allows to clean, filter and stucture the flight tracking dataset. Moreover, a trajectory clustering framework is applied to this data, given as result identified air traffic patterns at the terminal airspace as clusters. For each cluster, a nominal route is calculated. A detailed description of each step is provided next.

A. Data Description :

The raw dataset contains flight tracks from 7 days of august of 2018 obtained through the FlightRadar24 flight tracking service (FlightRadar24, 2019). FlightRadar24 is one of the various online flight tracking services made available after the introduction of new surveillance technologies in ATM, such as Automatic Dependent Surveillance - Broadcast (ADS-B). FlightRadar24 relies on a huge network of crowdsourced ADS-B receivers around the world that pick-up flight information (flight ID, aircraft position etc) broadcasted by the aircraft's ADS-B transponder and send this information to their servers to provide opensource live flight tracking. The raw datasets report one-minute updates of aircraft state, including flight ID, latitude, longitude, altitude, speed, origin airport, destination airport and aircraft type. Flight trajectories were then segmented according to the different flight phases. To extract the terminal area departure phase, we considered the trajectory information between the destination airport and the terminal area boundary, which was modeled as a circle of 40 nm radius with its center at the destination airport aka MohammedV.

B. Resampling

Data resampling is then performed to transform each time-series into a high dimensional feature vector of fixed dimension and enable the assessment of similarity between flight trajectories using standard Euclidean distance. The resampling approach normalizes the time stamps for each trajectory, divides it into a fixed number of equally sized time blocks and linearly interpolates the spatial position for the fixed number of normalized time stamps. The result is a feature vector of 2D spatial position evenly spaced in time.

C. Clustering at spatial scale:

The idea behind this framework is to identify spatial patterns of aircraft movement. Actualy, clustering is an unsupervised learning method that aims to identify groups of similar observations in a dataset without prior knowledge about the existence of these groups or about how the observations are distributed among them.

In this context, the goal is to find groups of similar trajectories in the spatial dimension. We define a group of spatially similar trajectories as a trajectory pattern.

This process requires then a data representation, a similarity/distance function and a clustering method. First of all , the portion of the trajectory associated with the airspace region of interest is extracted. In this case, to extract the terminal area phase, it was defined as the trajectory information between the airport runway threshold and the terminal area boundary, which was modeled as a circle of 40-mile radius with its center at the airport. The filtered flight trajectories are characterized by time-series of different lengths, depending on the time spent in the airspace volume.

DBSCAN algorithm :

The final requirement in the clustering methodology is the method for grouping similar observations. A density-based clustering algorithm – Density-Based Spatial Clustering of Applications with Noise (DBSCAN) (Ester et al., 1996) – is used for flight trajectory clustering. As the name of the algorithm suggests, this method is suitable for datasets with noise. In flight trajectory datasets, the standard routes and adaptions produce the core underlying patterns, yet abnormal trajectories can also occur for a variety of reasons and can be considered as noise. DBSCAN enables the identification of the core trajectory patterns in the presence of abnormal trajectory profiles. Other advantages of DBSCAN include the ability to discover non-convex clusters and no need to set the number of clusters a priori. DBSCAN relies on two input parameters in order to cluster the data space:

MinPts: a minimum number of points (observations);

ε: a distance threshold.

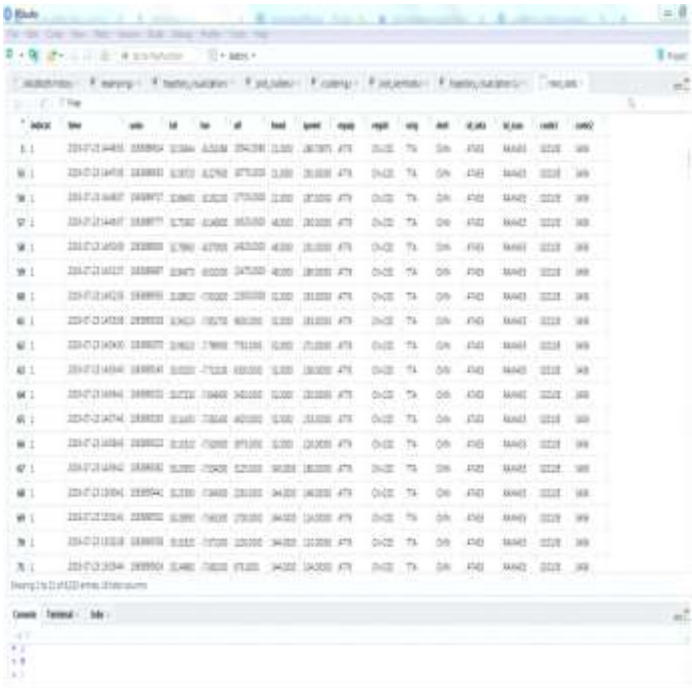
D. Results:

In the final step, the nominal routes are identified as a reference that could be used to measure both temporal or spacial efficiency.

Case study : Mohammed V Arrivals

In the last years, there is more talks about whatso-called “Big Data Analytics” since there is an increasing availability of data with new technologies (ADS-B: open-source flight tracking data “Flight Aware, FlightRadar24”) and as a consequence to it, opportunities to leverage the available system data for improved decision-making.

In our case, since the international airport of Mohammed V is known as the busiest airport of Morocco, we thought of a solution that will lighten the workload of its air traffic controllers by detecting the optimal arrival routes that pilots should follow. By this, we have provided a data that represents 7 days of collecting from FLIGHTRADAR24, from 23/07/2019 to 30/07/2019 focused on Mohammed V Arrivals. Those information were regrouped within an R program file called "track_data" where it was separated by indicators. We can see in figure 1 that it was the first flight collected starting from 2pm. It includes each position (longitude and latitude) it took during his flight inside the TMA until his landing. Aside from that, you find the heading, speed, equipment, registration, origin, destination, identification (IATA/ICAO), Squawk code.



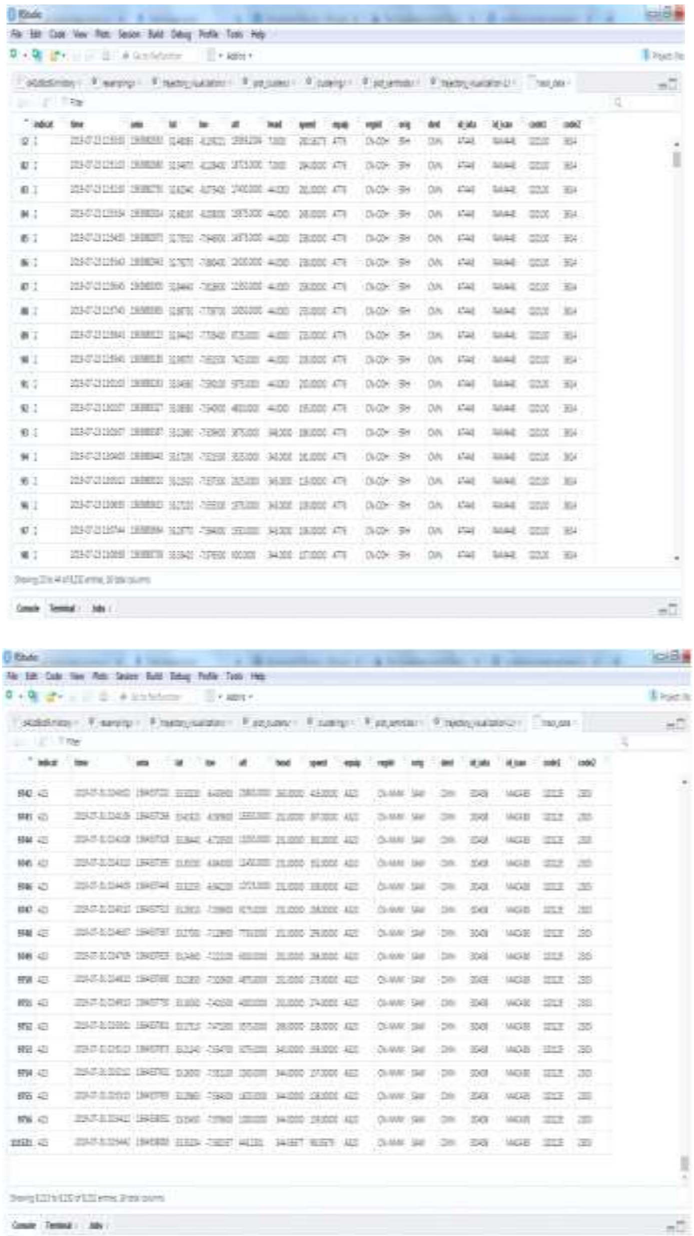


Figure 1 : Pieces of the collected Data of Mohammed V Arrivals

As it appears, when we move to another flight, the indicator changes but stay the same for the same flight and positions, time parameters keep on changing. Finally, for the last flight tracked on a week, it's the 423 one. This means that Mohammed V reaches only 423 per week. It is considerate as a big number in Moroccan but in comparison with some others international airports such as Guarulhos, Brazil that reaches twice the number of its traffic, it appears that the number is quite small. But in the other hand, Guarulhos has two operational runways where it is possible to do simultaneous departure and arrival which increase regulation facilities. Mohammed V has indeed two runways, but one of them is operational, the second is usually used as a taxiway.

After analyzing the data, it was possible to visualize the information within multiple steps:

a. **Trajectory visualization**

In order to visualize things in R and to, specifically, be able to plot same data, it is advised to use the package leaflet. You create a Leaflet map with these basic steps. Starting by creating a map widget by calling leaflet(), then adding layers (i.e., features) to the map by using layer functions (e.g. addTiles, addMarkers, addPolygons, addPolylines) to modify the map widget. Repeat step 2 as desired. Finaly, print the map widget to display it.

In this case, information are taken from track_data to print the trajectory of each flight all in once.

b. **Resampling:**

"Path resampling" process consist of a linear interpolation of the position made so that all paths can be described by a fixed-length vector.

INPUTS:

- track_data -> data frame with FR24 data
- NPOINTS -> indicates the desired vector size. For example, if NPOINTS =30, we will have 30 observations (lat, lon) describing the trajectory from terminal area entrance to airport arrival (40 nm). Since the FR24 data collection frequency is 1 min and the duration of flights in the terminal area is on the order of 30 minutes, NPOINTS = 30 is a reasonable resampling rate.

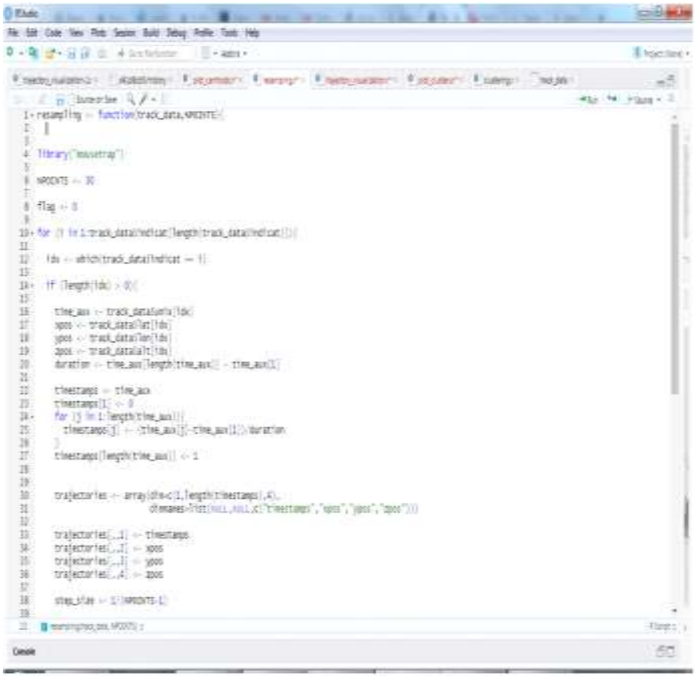


Figure 2 : Piece of the resampling coding

c. **Clustering:**

The process of clustering is based on DBSCAN Algorithm. After resampling trajectories, they are now ready to be compared. We apply to them the DBSCAN algorithm, and wait to see how much clusters these trajectories has been separated from each others. In order to guess the number of the clusters, the easy way is to visualize them.

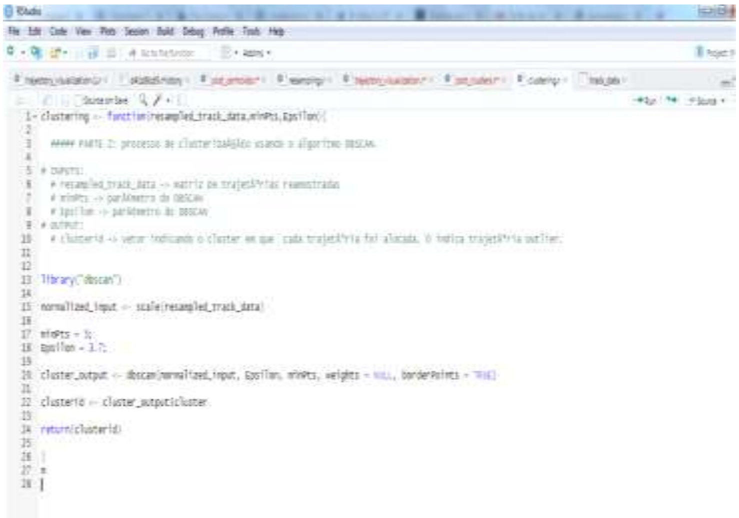


Figure 3 : Rcode for clustering

Figure 4: ploting and visualizating clusters.

It appears that there are four different colors which means four clusters, each one oriented toward a direction. This only mean that there are basically four ways to reach the airport of Mohammed V that the aircraft could take.

d. **Centroids:**

After the clusters of trajectories are identified, a nominal route is determined for each cluster by solving a 1-median problem, in other words, a representative trajectory for each cluster is obtained by calculating the “center” of the cluster. For each nominal route associated with a cluster, an unimpeded flight time is calculated as the 10th percentile of the distribution of flight times observed for the members of the cluster. The nominal routes are defined as the reference ideal trajectories with which actual trajectories are compared in order to characterize performance, those nominal routes are known as centroids.

As of fact, four centroids are clearly distinct and represents the ideal trajectories.

Figure 5 : visualization of centroids

Conclusion

In this article, we used a data-driven approach for characterization of the Casablanca, Morocco airspace structure and air traffic operational performance from aircraft tracking data recorded by surveillance systems. Unsupervised learning is performed associated with a flight trajectory clustering analysis to automatically identify spatial traffic patterns in terminal airspace of Mohammed V, Casablanca airspace. Based on the as-flown route structure learned, quantitative metrics could be developed to describe the structural efficiency of the airspace and the operational efficiency of the traffic flows. For this, actual flight trajectories can be projected onto reference nominal trajectories in space and time. The results allowed above can permit a cross-route comparisons of air traffic flow efficiency across the terminal phase of the flight as well as for the other phases. An interactive data analytics tool is also created to output performance statistics and air traffic visualizations.

References

1. International Air Transport Association. IATA forecasts passenger demand to double over 20 years. http://www.iata.org/pressroom/pr/Pages/2016-10-18-02.aspx (12-05-2019).
2. Lee, J. G.; Han, J.; Whang, K. Y.: "Trajectory clustering: a partition-and-group framework". Proceedings of the ACM SIGMOD International Conference on Management of Data, pp. 593-604, 2007.
3. Kim, J.; Mahmassani, H. S.: "Spatial and temporal characterization of travel patterns in a traffic network using vehicle trajectories". Transportation Research Part C: Emerging Technologies, Vol. 59, (2015), pp. 375-390.
4. Antonini, G.; Thiran, J. P.: "Counting pedestrians in video sequences using trajectory clustering". IEEE Transactions on Circuits and Systems for Video Technology, Vol. 16 nº 8 (2016), pp. 1008-1020.

5. Eckstein, A.: “Automated flight track taxonomy for measuring benefits from performance-based navigation”. Proceedings of the Integrated Communications, Navigation and Surveillance Conference, pp. 1-12, 2009.
6. Gariel, M.; Srivastava, A. N.; Feron, E.: “Trajectory clustering and an application to airspace monitoring”. IEEE Transactions on Intelligent Transportation Systems, Vol. 12 nº 4 (2011), pp. 1511-1524.
7. Rehm, F.: “Clustering of flight tracks”. Proceedings of the AIAA Infotech@Aerospace Conference, 2010.
8. Enriquez, M.: “Identifying temporally persistent flows in the terminal airspace via spectral clustering”. Proceedings of the 10th USA/Europe Air Traffic Management Research and Development Seminar, 2013.
9. Murça, M. C. R.; Hansman, R. J.; Li, L.; Ren, P.: “Flight trajectory data analytics for characterization of air traffic flows: A comparative analysis of terminal area operations between New York, Hong Kong and Sao Paulo”.Transportation Research Part C: Emerging Technologies, Vol. 97 (2018), pp. 324-347.