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ARTIFICIAL INTELLIGENCE TOOLS FOR THE COVID-19 ASSESSMENT ON AIRLINES: ECONOMIC IMPACT AND RECOVERY

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Abstract

Although the aviation sector had previously shown strong resilience to overcome different crisis, the COVID-19 pandemics has severely impacted it and the airlines' current economic situation poses difficult challenges to survive. Given the increased popularity of Artificial Intelligence (AI) algorithms, this study proposes a method based on unsupervised learning, particularly Self-Organizing Maps (SOMs), in order to quantitatively analyze the economic evolution of the airlines as well as to potentially assess actions to accelerate the recovery. Specifically, the main indicators from the financial statements of the top 5 European airline conglomerates during the last 6 years are considered in this work.

1. Introduction

Although most of its related fundamentals, algorithms and tools have been known for decades, Artificial Intelligence (AI) had not been widely spread until the 2010 decade (Russell & Norvig, 2016). This is due to the increased computing power as well as the collection and storage of large amounts of data, two key aspects required for the development of this kind of models.

However, despite the high potential of these new technologies and the high number of academical developments and research in the field (Pérez-Campuzano *et al.*, 2019), their practical implementation is still at a very early stage and there is still room for improvement for organizations in order to achieve a proper digital transformation (Camus Moller *et al.*, 2019).

This technological transformation has already been addressed by different industries and sectors. For example educational and entrepreneurial technologies were explored by (Costa *et al.*, 2017), applications within the renewable energy industry were analyzed by (Pérez-Campuzano *et al.*, 2016) and an innovative value chain was proposed for the banking sector in (Bueno *et al.*, 2017).

Within the transportation sector and particularly regarding airlines, strategy and technology have been identified as critical factors for the definition of their business models (Sengur & Sengur, 2017), which are mainly divided between Full-Service Network Carriers (FSNCs) and Low-Cost Carriers (LCCs). The increasing interest on this type of technology can be observed in Figure 1, which represents the scientific production in this area through the last 45 years.

As Figure 1 shows, in the 70's and 80's, 22 early works were already published including the AI topic within the Transportation area. After that, the AI popularity steadily grew between 1990 and 2010. Eventually, this interest exponentially increased during the last decade with a 34% CAGR.

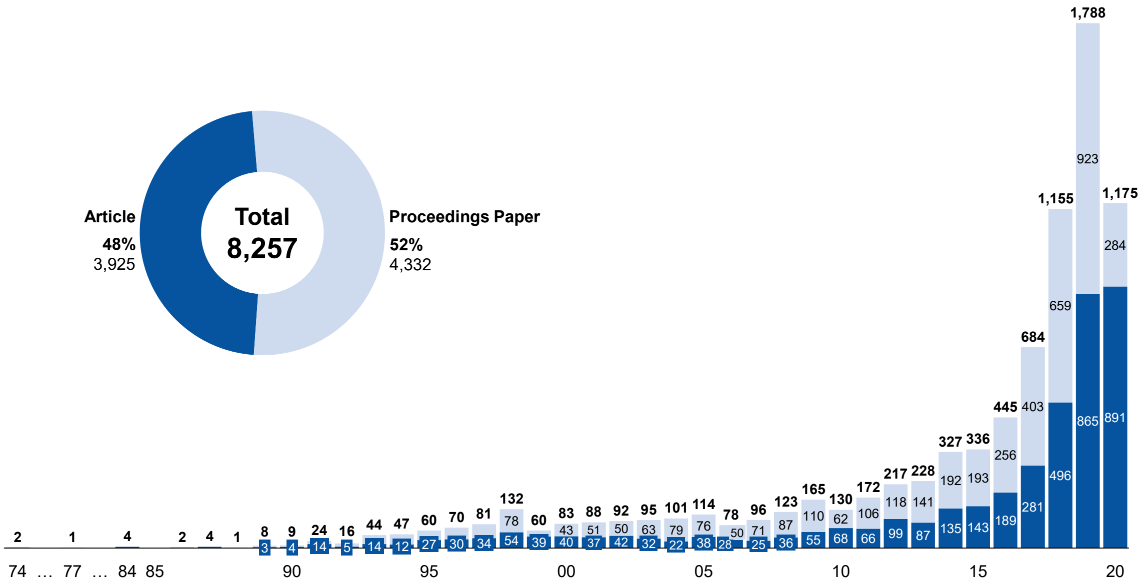

Figure 1. Historical evolution of publications including the topic "Artificial Intelligence" within the research area of "Transportation". Elaborated with data from the database by ISI Web of Science.

However, the COVID-19 pandemic put a halt to this historical growth in 2020. During this year, authors barely managed to slightly surpass the 2019 figures in terms of published articles (+3%) while the number of proceeding papers sunk year over year (-69%). This is probably a consequence of the number of conferences cancelled along 2020 due to reduced mobility and social distancing policies. This has balanced to some extent the historical ratio of articles versus proceedings papers, which was slightly biased towards the latter until 2019 (43%/57% by 2019 and 48%/52% by 2020).

But obviously the scientific production has not been the only area affected by this critical situation. The air transport sector had shown great resilience to past crisis such as the 11S, SARS outbreak, 2008 global economic crisis and, more recently, Brexit as analyzed in (Sehl, 2020) and (Torrejón Plaza *et al.*, 2019) . However, the COVID-19 has severely affected the flight operations (commercial scheduled, cargo and business) mainly due to the mobility restrictions enforced (EUROCONTROL, 2020). This shock along with the consequent new social and labor habits established after the outbreak (Amankwah-Amoah, 2020; Maneenop & Kotcharin, 2020) as well as environmental and climate change concerns (López-Lázaro *et al.*, 2018) pose substantial challenges to the airline industry and its organizations (Bolat & Ateş, 2020).

This paper analyzes the current situation and trends regarding the economic impact of the COVID-19 on the top 5 airline groups in Europe and also proposes an AI-based model using Self-Organizing Maps (SOMs) in order to visualize the market environment. The objective of this work is threefold: to support the practical deployment of AI algorithms for economic applications, to assess the COVID-19 impact in the aviation industry in comparison with the historical market trends and to help on the identification and assessment of potential strategic actions for the economic recovery.

2. Methodology

A Data Mining method (Tan *et al.*, 2013) based on unsupervised learning is proposed in this section with the goal of quantitatively assessing the economic impact of the COVID-19 crisis as well as enhance the decision-making process for airlines. The general scheme of the process is shown in Figure 2 and further described in the following paragraphs.

Figure 2. General scheme for the AI method based on unsupervised learning.

Firstly, as most of data science related works, a preprocessing stage should be conducted in order to properly gather, clean and organize the collected raw data prior to feeding the model (Han *et al.*, 2012). Normally this stage includes steps such as cleaning, integration, reduction and transformation.

Once the input data has been prepared, the model engine has to be designed. In this case, the unsupervised clustering algorithm employed is a Self-Organizing Map (SOM), firstly proposed by (Kohonen, 2001). The rationale behind the selection of this engine is that it is constituted by a neural network that, in addition to clustering the individuals, defines a topologic relation between the nodes or neurons of each cluster. In contrast with other clustering algorithms, SOMs allow to make a 2D representation of the data according to this topology, which eases the visualization and analysis.

Additional knowledge can be also extracted from the relative position between the individuals after being distributed along the map. The visualization of the neuron weights of the SOM is also useful for understanding the underlying structure of the map. These weights represent the network parameters which are optimized during the model training and which, once their values are fixed, will determine in which neuron the individuals are allocated according to the values of their variables or attributes.

Once the model is trained, one possible use case consists on feeding the model with new individuals representing future estimates or potential strategic actions (both for the own organization or other competitors). By doing this, the different alternatives could be assessed and compared in order to identify those with the most beneficial impact for the company. This represents an opportunity to preliminarily assess potential actions for the economic recovery after the pandemics.

3. Data

The raw data for this study has been extracted from the financial statements of different airlines and has been subject of a stringent preprocessing according to the steps mentioned in the previous section. In this case, the data analyzed comprises economic figures for the last 6 years (2015-2020) of the top 5 airline groups based in Europe:

- **Full-Service Network Carriers (FSNCs, 3):** Lufthansa Group (LHG), Air France - KLM Group (AKG) and International Airlines Group (IAG).
- **Low-Cost Carriers (LLCs, 2):** Ryanair (RYR) and easyJet (EJU).

On the other hand, the 9 variables selected as inputs for the model developed in this work include diverse information from the financial statements:

- **Profit & Loss (4):** Revenues, EBITDA, EBIT and Profit.
- **Balance sheet (5):** Current assets, Non-current assets, Current liabilities, Non-current liabilities and Equity.

As a preliminary analysis of the input data and also as a way to compare the size of each of the airline conglomerates, Figure 3 shows their corresponding revenues for the 6 years under study.

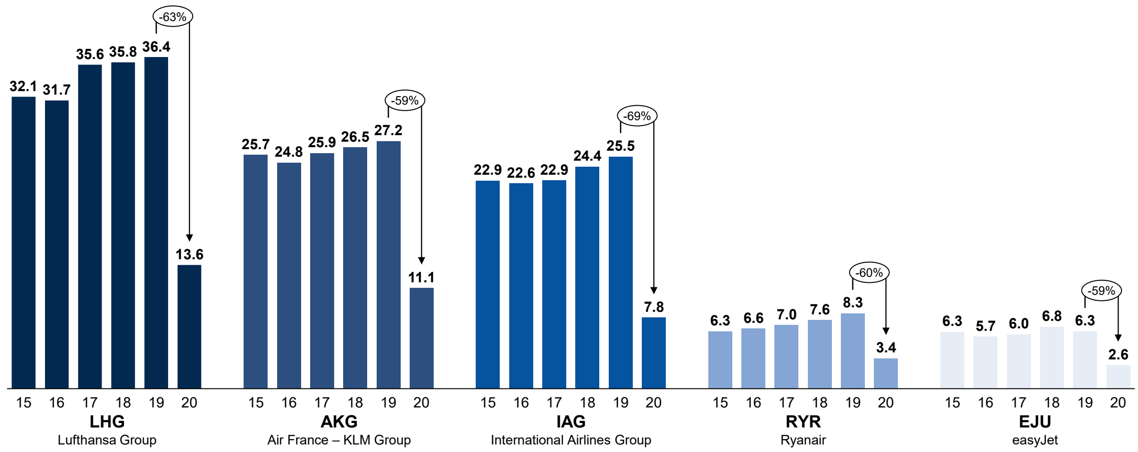

Figure 3. Revenue evolution for the 5 airline groups (€bn).

The main observation from the comparison in Figure 3 is the difference in scale between the 3 major groups (with revenues in the order of €30bn) and the 2 LCCs (with revenues in the order of €7bn).

The shock caused by the COVID-19 (approximately -65% in revenues for all the groups) is also clearly visible. The pandemics has halted the stable growth the air transport was experiencing during the previous years. It must be pointed out that the impact of the outbreak started to be noticeable by these European airlines by the end of February or beginning of March; hence, most of that decrease in sales was caused only during the last 10 months of the 2020 year.

Additionally, Figure 4 shows the Balance sheet for each of the conglomerates. Once again, the COVID-19 impact is clearly visible, especially for the 3 major FSNCs whose debt ratio has increased in a noticeable way. However, the 2 LLCs managed in 2020 to maintain their balance structure very similar to the one in 2019. This signals the higher flexibility and resilience of this kind of business models against disruptions in the market or its environment.

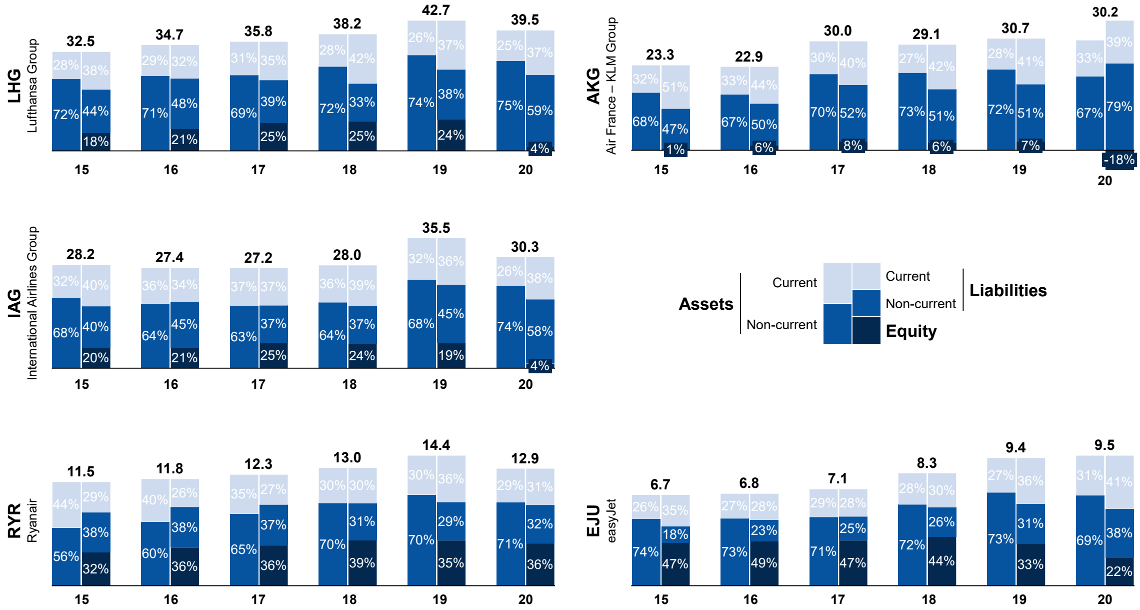

Figure 4. Balance sheet evolution for the 5 airline groups (€bn).

4. Results

Once the individuals and their attributes are collected and preprocessed, they are fed into the unsupervised Data Mining algorithm, a Self-Organizing Map (SOM) with a 7x7 network of 49 interconnected neurons in this case.

During the training stage, the network parameters (neuron weights) are optimized in order to adapt the 2D network within the multidimensional space of inputs and try to match the structure of the input data. Figure 5 shows the result of this stage in which each individual (represented by each correspondent airline 3-letter code and 2-digit year) has been eventually allocated to the different neurons of the network.

The results of the AI model allow to extract potential conclusions regarding the economic impact of the crisis in the airlines. Particularly, in Figure 5, the evolution of the airlines and the relative relationships between them can be observed as a result of the automatic allocation of individuals through the 7x7 network. Straight lines between neurons of consecutive years for the same airline have been also represented as connectors a posteriori in order to ease the visualization of the trajectory of each of the carriers throughout the map and along the years.

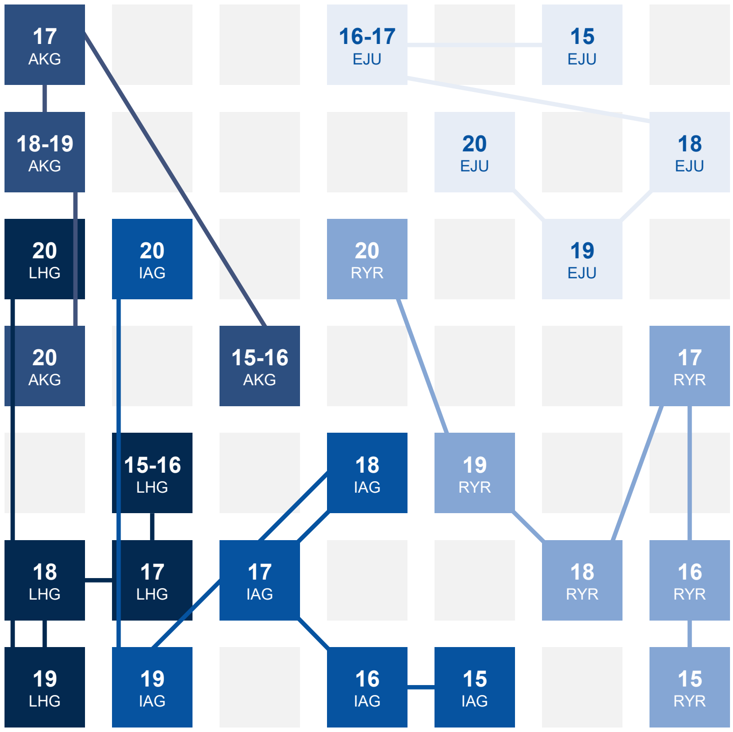

Figure 5. Allocation of individuals (airline and year) to each of the neurons of the Self-Organizing Map (SOM).

The first observation is that the SOM has automatically and intrinsically divided the map into two main triangular halves which are separated by the main descending diagonal from top-left to bottom-right. Both LCCs (RYR and EJU) have been allocated in the top-right triangle while the FSNCs (LHG, AKG, and IAG) have been distributed along the bottom-left portion of the map.

It is also noticeable how, while each of the airlines were scattered across each of the areas, the individuals corresponding to 2020 have been allocated in very specific and well-delimited zones. The consequences of the COVID-19 can be also analyzed by measuring the distance between the neuron where the 2019 individual was allocated and the corresponding to year 2020. In the previous seasons the year-over-year movements were usually to consecutive or near neurons. Nevertheless, the 2019-2020 jump is in most of the cases the highest for each of the carriers. This is especially observable in the case of LHG and IAG which moved in parallel 4 neurons upwards from their previous allocation in the bottom-left corner of the map in 2019. An exception to the disruptive displacements from 2019 to 2020 is the easyJet case, which only moved to a consecutive diagonal neuron.

This distribution of the different individuals can be further understood by analyzing the intrinsic architecture of the network. With this purpose, Figure 6 shows the weights of each of the 9 input variables for each of the 7x7 neurons in the SOM. Its analysis can help on understanding the underlying structure of the industry as well as the similarities between airlines from an economic point of view.

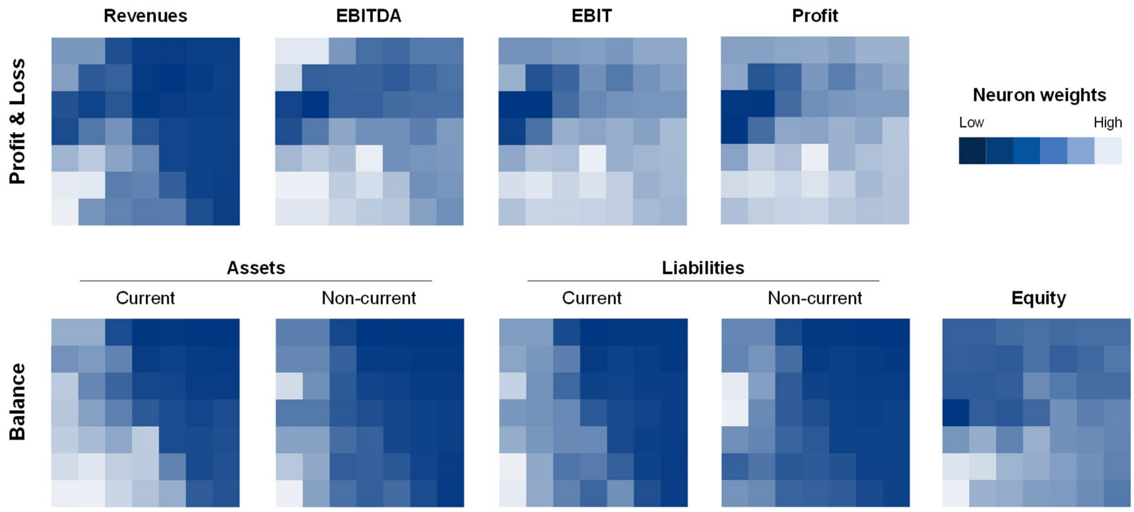

Figure 6. Weights of the 9 input variables for each of the 7x7 SOM neurons.

In the case depicted in Figure 6, it seems relatively clear that the aforementioned segregation into 2 triangles (delimited by the descending diagonal) responds mainly to the differences in Revenues as well as in Assets and Liabilities. In fact, the maps corresponding to these variables show a topology which resembles that distribution (with lower weights in the top-right area and higher weights in the bottom-left region)

The structure of the rest of variables (EBITDA, EBIT, Profit and Equity) does not show a clear relationship with those two main triangles. However, some outliers are noticeable such as the 3 dark neurons which correspond to the 2020 individuals for the three FSNCs whose profitability was highly impacted due to the pandemics. This also corresponds to the high values of the weights for the Non-current liabilities in the neurons where the 2020 individuals of LHG and AKG were allocated. This is explained by the increment of debt that these groups had to incur due to the operational challenges of that extraordinary year.

It is also worth mentioning the high-value outlier in the EBITDA, EBIT and Profit indicators that corresponds to the RYR 2019 neuron (see Figure 5). They underline the high performance in terms of profits that Ryanair achieved in that year compared with its pairs and with other seasons. In addition, that was the case in which any of the 2 LCCs were closer to the FSNCs area in the map (note that IAG 2018 was in a successive neuron).

5. Conclusions

This paper analyzes the current situation and trends regarding the economic impact of the COVID-19 on the top 5 airline groups in Europe and also proposes an AI-based model using Self-Organizing Maps (SOMs) in order to visualize the market environment. The objective of this work is threefold: to support the practical deployment of AI algorithms for economic applications, to assess the COVID-19 impact in the aviation industry in comparison with the historical market trends and to help on the identification and assessment of potential strategic actions for the economic recovery.

After collecting and preparing the financial data of the 5 conglomerates, a preliminary analysis of the information during the last 6 years allows to observe the magnitude of the COVID-19 impact. Specifically, the revenues fell approximately -65% for the 5 airlines. On the other hand, the Balance sheet of the 3 major FSNCs was also modified mainly by increasing the debt ratio versus the Balance structure of the previous years. On the other hand, the LCCs seemed to show higher resilience as their Balance structure did not suffer major changes.

The application of the AI model (a 7x7 SOM in this case) to the aforementioned inputs allows to visualize the market evolution of the competitors as well as the relative relationships between them. Some of the observations are related to the capability of the model to automatically discern between business models and to visualize the effect of the pandemics for the different airline groups. A deeper analysis based on the intrinsic structure of the network (neurons weights) can increase the wisdom extracted from the data and gives more visibility on the underlying market constraints.

The proposed model can further be applied to different use cases such as the estimation of future evolution of the competitors as well as the assessment of potential economic strategies to be enforced in order to accelerate the economic recovery. Additionally, the case can be expanded to other players or sectors and include other input selection processes such as those presented in (Pérez-Campuzano *et al.*, 2018) or clustering algorithms (Han *et al.*, 2012).

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