University of Warsaw
Faculty of Economic Sciences

Michał Kunstler 412032 | Jarosław Leski 411174 | Artur Skowroński 411423 | Daniel Śliwiński 405848

# Upgrading predictions - analysis of class upgrades for airline passengers using XAI enhanced LightGBM

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## Abstract

The goal of this study is to model the propensity score to upgrade class for an airline passenger. Furthermore the paper explores the novel XI techniques by comparing the results from interpretations of econometric models and LightGBM. The data was provided by PLL LOT S.A.. The analysis shows that XI offers robust explanations for the machine learning model, which outperforms econometric counterparts in both classification and regression. The models identify that the most important variables for the propensity to upgrade are the flight distance and the booking window.

## Keywords

Upgrade of tickets, Airlines, Explainable AI, LightGBM

## 1. Introduction and literature review

The vast majority of passengers that decide to travel by air choose the economy class. The main reason for that is the relatively high cost of travel by plane. For some of them classes of higher standards may be simply unaffordable. For others traveling to a certain destination may just be a necessity not worth the extra benefits. But what about the customers that could potentially consider upgrading their tickets?

Many customers are not even aware of the possibility to upgrade their tickets. However notifying each customer of such possibility would lead to excessive decline of customer experience. The reason being is that the passengers are already receiving a large number of messages before the flight. The other one is that most passengers are not willing to bear any additional costs of the travel (Kuo, Jou, 2017). Therefore careful selection of potential customers is crucial in order for this campaign to become successful. Such analysis also brings up another question: what’s the optimal time for notifying the customer of the aforementioned possibility?

The difference in price between economy and business class is usually very significant. There’s however the middle option which was first introduced in the 90s: premium economy class. Such an upgrade is cheaper than business class and results in a substantial increase in comfort, which becomes of great importance, especially when it comes to long-haul flights. Existence of premium economy class does not only increase the profitability of the carrier company but also enhances the airlines' load factors and competitiveness between firms (Kuo et al., 2017). Hugon-Duprat and O'Connell (2015) found that a premium economy class seat is only 1.6 times more expensive in production than the economy one, while the revenues generated from it are 2.3 times higher than the cost of production. Economy class produces only marginal returns. Business class has the highest potential of generating profits for the companies, however its low loading factor decreases the returns on investment. Assuming a high loading factor of premium economy seats, increasing their number may lead to maximization of profits. These findings stress the importance of detecting the flights and bookings that have the highest chance of being upgraded by the customers. We anticipate that the most upgrades are to be achieved from the economy to premium economy class.

Passengers that cannot reserve the economy window or aisle seats are more likely to buy a premium economy seat (Mumbower, Garrow, Newman, 2015). This may suggest that passengers having the slightly less comfortable seats in the regular economy class, may be more likely to buy an upgrade. It would be also consistent with the findings, that passengers' willingness to pay (WTP) for aisle and window seats is higher than for the regular seats in the economy class (Weinstein, Keller, 2012).

Due to the higher comfort of sitting next to an aisle or window, these seats have a higher chance of being bought by the customers first. What follows is the difficulty for the traveling families to sit together. This issue could be resolved by introducing higher fees for higher demanded regular economy seats, however extra fees tend to lower the customer satisfaction levels while selecting the seats. Consequently, charging the families higher fees for sitting together does not seem like a good solution either (Mumbower et al., 2015). Therefore it may be the case that passengers traveling with children may be more likely to upgrade their tickets to premium economy seats, which have lower loading factor than the regular economy ones. Families may derive higher utility from traveling together in a class of higher standard, while at the same time not feeling that the higher fee is unfair, as they could enjoy other benefits such as priority in baggage reclaim or priority boarding. Both of these services could be highly appreciated by parents traveling with their children.

Customers, which buy their tickets closer to departure date tend to be less price sensitive and may pay more for seat fees (Mumbower et al., 2015). This may however not be the case when it comes to upgrading a ticket. It could be that the customers who book their flights a relatively long time before the departure, may be more likely to upgrade their tickets a few days before the flight. The reason being that the costs would be spread over time and the additional costs would be felt differently by the customers.

Length of travel may also be a significant factor in the analysis. According to Kuo & Jou (2017) and Jeon & Lee (2020) findings, the longer the trip, the more passengers' WTP for a ticket upgrade from economy to premium economy class. Clear understanding of obtained benefits from an upgrade seems to have a positive impact on the willingness to upgrade as well. Furthermore, they claim that passengers aged 51 and above may also be more likely to upgrade their tickets, for the comfort of travel is of bigger importance for the elderly. It could be also anticipated that the elderly may be more prone to not knowing about the upgrade possibilities.

Travelers may upgrade their tickets through buying a higher class or through buying additional services such as priority boarding or extra luggage. Our hypothesis is that those passengers who have already bought the additional services are less likely to buy a *bigger* upgrade in the form of a higher class ticket. The reason being that the purchase of a bigger upgrade in that case would no longer be appealing to the passenger. For example if they would already have priority boarding and additional luggage in the normal economy class, there is a good chance that they would not be interested in the remaining premium economy class benefits such as choice of seat or premium meals.

The goal of this paper is to predict which bookings and flights have the highest propensity score for purchasing the upgrade of an already bought ticket. Additionally, the paper aims to analyze the differences between the predictions made by econometric and machine learning algorithms, by leveraging novel explainable AI tools. To this extent, a second modeling process will be performed, with its goal being the prediction of the optimal time before a flight to offer a customer an upgrade. This will allow us to perform the comparison on both classification and regression problems.

The first part of the paper will discuss the methodology, where the utilized algorithms, XAI and the used model performance measures will be elaborated upon. The second part will contain information about the dataset. In the third part the results of the empirical experiments will be described for all of the models. The last part will summarize the most interesting finding as well as propose some possible improvements to the methodology and further research opportunities in this topic.

## 2. Methodology

2.1 Utilized algorithms

In order to perform the comparison between the results derived by the most often used algorithms in business, being whitebox models and the state of the art machine learning solutions, the models have to be correctly selected. The binary classification was attempted using logistic regression, random forest and LightGBM. Logistic regression (LR) is by far the prevailing algorithm for binary classification in business. It is relatively simple to perform, fully interpretable and it performs relatively well when compared to more modern solutions (Pesantez-Narvaez, Guillen, Alcañiz, 2019; Xu, Han, Huang, 2022). Random forest (RF) is one of the more “traditional” machine learning algorithms. It is an ensemble of decision trees and is often used as a benchmark for the more novel ensemble models, as well as also often being utilized in business. It is however considered a blackbox model. The last algorithm which tackles the classification problem is LightGBM. It is one of the newer algorithms based on the gradient boosted decision tree architecture. It was released in 2016 by Microsoft, along with several researchers, during the rise of popularity of GBDT based models initiated by XGBoost. The algorithm is quite similar to the aforementioned XGBoost, however due to some optimizations it requires much less computational power compared to its predecessors, computing power requirement being one of the main weaknesses of XGBoost when compared to RF.

For the regression problem, the linear regression (LR) will be representing the whitebox models, being probably the most often utilized model out of all statistical and machine learning methods. The linear regression performance will be compared to the performance of RF and LightGBM, as both of these models also have regression problem solving capabilities. RF is often considered a tool better for classification than for regression, however numerous researchers have shown that RF is more than capable of performing well in a regression problem (Segal, 2003).

## 2.2 Explainable Artificial intelligence (XAI)

In recent years, there has been a lot of progress in developing the explainable AI methods, with more emphasis being put on this subject and new innovations being developed at an increasing pace. One of the reasons for the newfound popularity of XAI is that the business is becoming increasingly interested in ML solutions, however it is difficult to adapt to them, when they are based on unexplainable blackbox models. This is the case mostly due to negative pressure from regulators and other stakeholders. XAI, presents a new avenue of accessing the predictive power novel ML models, without (or with very limited) compromises in the interpretability investigates solutions. This trend may be the deciding factor in the efficiency of the analytic operations of most markets, and therefore be one of the most important drivers of profit for companies worldwide.

One of the most powerful XAI packages available for free is dalex (Biecek, Burzykowski, 2021). The package can be used with R or with Python, and it contains several interesting methods of explaining ML models. In this paper, two features of this package are leveraged: dataset-level variable importance measures and dataset-level partial dependence profiles. The variable importance measures implemented in this package are based on ones developed by Fisher, Rudin and Dominici (2019). They measure the impact on the model overall, with a particular variable removed, in order to estimate its importance. The developers of the package establish that this method of measuring variable importance is at the same time effective and model agnostic, meaning that it is universal for multiple types of models. The partial-dependence profiles (PDPs) are intuitively described as objects describing the relationship between the expected target response and any number of selected independent variables. Usually, a PDP of one or two variables at a time is analyzed, due to the constraints of readable presentation methods (more than 3 dimensions being very tough to visualize). PDPs work best for continuous variables, as for binary variables they yield results quite similar to variable importance analysis.

With these tools, it is possible to extract the most relevant information from a blackbox model. It should be minded that these tools do not provide these models with the full explanation capabilities of statistical models, but oftentimes they may be considered specific and thorough enough.

2.3. Assessment of prediction quality

The measure used to determine the predictive power of the models is the ROC AUC score. It is considered to be one of the best methods for evaluating binary classification accuracy. The name ROC curve is an abbreviation for “Receiver Operating Characteristic”, which is the ratio between true positive rate and false positive rate at different threshold levels. The AUC, on the other hand, is the area enclosed by the ROC curve and a straight line with a slope of 0.5. Its value is between 0 and 1, where the closer to 1, the higher the percentage of the correct estimations (Matjaž, Bosnic, 2011).

## 3. Materials

3.1 Dataset

The dataset used in this paper was an actual, anonymized flight booking data of PLL LOT S.A. airline passengers. The main challenge of pre-processing the dataset was the decision to disaggregate the data into the coupon level. A passenger making a reservation had a unique reservation (booking id) number created. A given booking id could contain several tickets (many passengers assigned to one reservation), and then each of them could contain information about coupons. The coupon can be understood as information about a specific trip of a specific passenger with specific parameters. The decision was made to explain the dependent variable of buying an upgrade to a higher class of travel at the level of the coupon.

In the process of data preparation, information about passengers purchasing other forms of upgrades was also included. They are important because they are 'competitors' for the explained variable.

We can categorize the variables used in the models into 5 groups:

1. Reservation parameters: Month and day of the week of the booking, how long since the start of the trip the booking was made, channel of the booking (whether through PLL LOT S.A. or external Agents), number of coupons per booking.
2. Ticket parameters: ticket price, whether the adult passenger was traveling with a child, whether the journey was a business trip, whether the ticket belongs to a passenger who is a member of a loyalty club, the currency in which the payment was made.

3. Coupon parameters: flight quarter and day of the week, flight departure time, flight length in kilometers, initially purchased flight class, tariff category.
4. Additional service parameters: binary variables - whether services such as baggage, carriage of additional equipment, carriage of pets, seat selection, meal order or others were added to the booking.
5. Calculated parameters: share of additional services in the ticket price, how many days before departure additional services were purchased or class upgrade was performed.

Almost 95% of passengers buy economy class tickets. In addition very few customers decide to upgrade their tickets in any aforementioned way. Therefore the dataset is significantly unbalanced, for the not upgraded coupons constitute the vast majority of the data. These factors must be accounted for in the analysis.

## 4. Empirical study

Due to the time constraint and limitations in computational power which were present when performing this study, the modeling process had to be limited in scope. It turned out that random forest was far less time-efficient than LightGBM, and therefore it would not be possible to perform full analysis using both algorithms. Due to the object of the study being the comparison of older statistical methods to newer machine learning methods, it has been decided that LightGBM will be representing the newer algorithms. This allowed for much more aggressive hyperparameter optimization, and therefore allowed for the algorithms to be as efficient as possible. The optimization was performed using random search with 2-fold cross-validation, as implemented by the SciKitLearn Python library.

### 4.1 Classification

Identification of passenger propensity to upgrade was the main “business” objective of the study, so naturally classification was much more heavily invested into than the regression problem. The dataset used for classification problem was very unbalanced, with the non-upgraded coupons representing roughly 98% of the dataset, and only 2% of observations being upgraded coupons. These are the proportions after the number of non-upgraded coupons was cut by 95%, by random sampling. Nevertheless, due to the use of the aforementioned AUROC score as the main scoring measure, this did not hinder the training process of the algorithms, and thanks to the use of that measure, the results presented have the unbalance of the data accounted for.

**Figure 1. AUC for final models constructed by logistic regression and LightGBM**

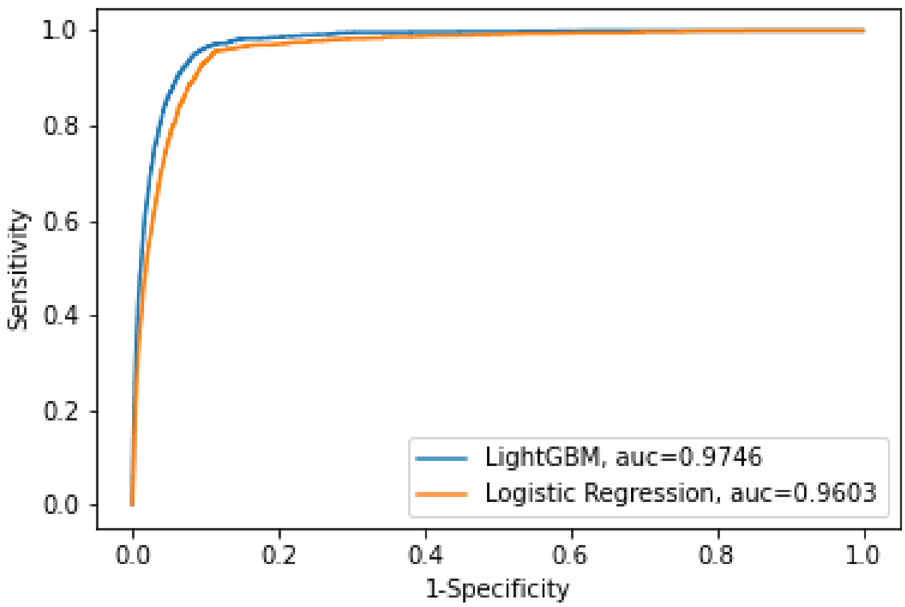



Figure 1. presents the AUCs of both of the final models used in classification. Due to the nature of the dataset at hand, the AUROCs were relatively high regardless of the algorithm used, but still it is clear that as far as predictive power goes, the LightGBM has outperformed the logistic regression. This comes as no surprise and is consistent with the scientific consensus.

Both LightGBM and Logit model yielded somehow similar and yet a bit different variable importance results:

**Figure 2. Variable importance for LightGBM Classifier**

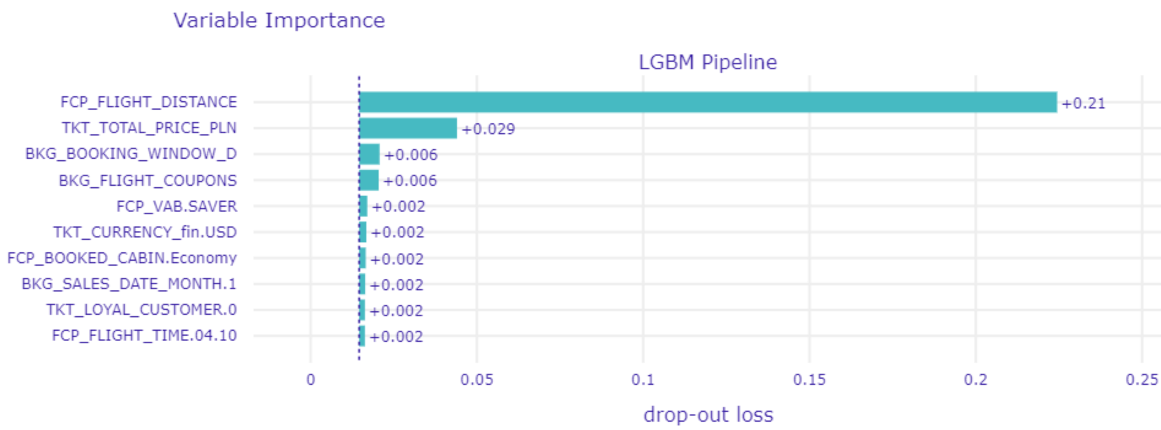
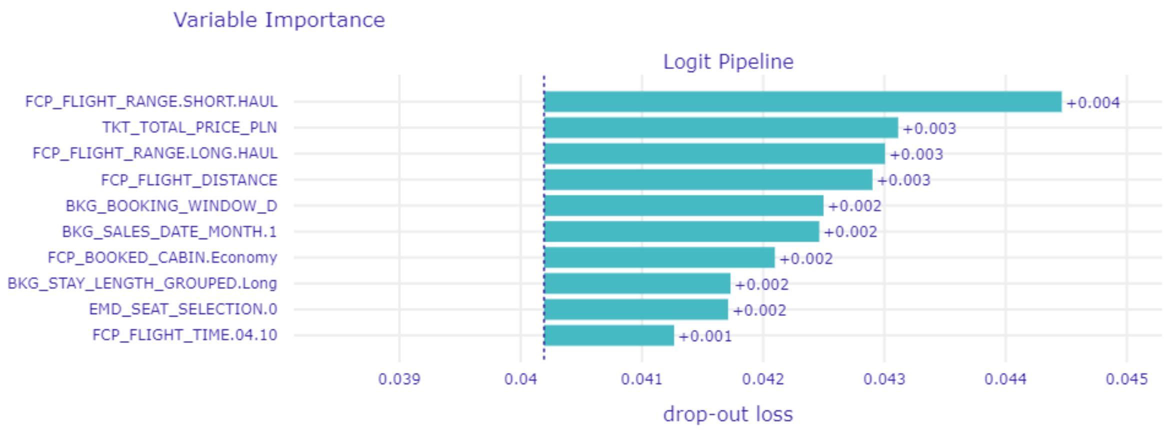


**Figure 3. Variable importance for Logistic regression**




In the LightGBM the most important variables are the flight distance and the total price of a ticket. Booking window and number of flight coupons also stand out from the other important variables. In the logit model the importance of variables is less dispersed. Short-haul flight seems to be of the biggest importance, while total price, long-haul and flight distance are the close followers. In both models month of the booking and the economy class factors are significantly impacting the propensity score as well.

Partial-dependence profiles are also similar between the models.

**Figure 4. Partial-dependence profiles for LightGBM Classifier**

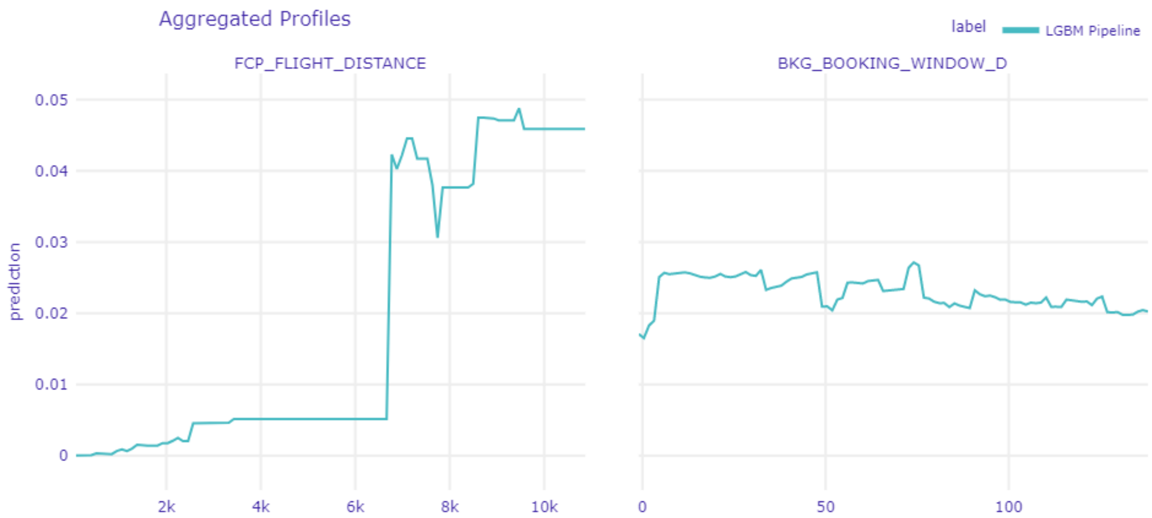
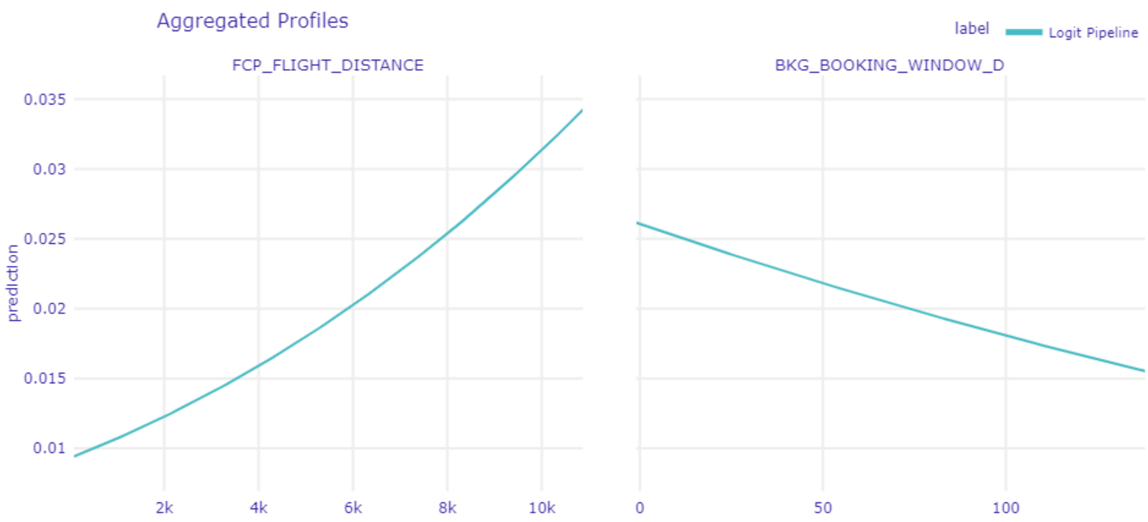


**Figure 5. Partial-dependence profiles for Logistic regression**




Flight distance affects the propensity in a similar fashion in both models. There is however a noticeable difference in the shape of the curves. The logit one is by default more smooth than the other one. The sudden rise of the flight distance curve in the LightGBM clearly shows the sharp difference between short-haul and long-haul flights. The interpretation is noticeably different between models when it comes to the booking window. In the logistic regression the interpretation would be that the more distant in time is the departure from the booking date, the less likely is the customer to buy an upgrade. From the LightGBM findings may be inferred that the passengers who book the flight right before the departure or very far from it, are less likely to buy an upgrade. Passengers who book a flight between 10 to 70 days before the flight are more likely to upgrade their tickets. The interpretation here could be that people who book flights long ahead of the departure, may care more about saving money as much as possible rather than enjoying the comforts of the flight. The passengers who book flights right before the departure could also focus on saving through choosing last minute flights. The other ones may be suddenly forced to travel by plane and also not care about the possibility of an upgrade. In this model, the sweet spot would be somewhere in the middle, but definitely excluding the marginal values of the booking window.

4.2 Regression

The secondary business objective of the paper was to establish the optimal time to offer to upgrade the ticket for each customer. This dataset contained only the coupons which have been upgraded, however it was still plagued with serious problems. We concluded that there were probably some mistakes in the data, as it suggested that the upgrade for several hundred coupons was purchased days after the departure of the flight. Keeping in mind that it is either exemplary of data problems, or of very dubious decisions undertaken by several hundred customers, these observations were excluded from the analysis. The regression models contain differing numbers of variables, as some of them have been excluded for the linear regression model as they were deemed statistically insignificant. The performance of the models is presented in Table 1.

**Table 1. The performance of the models**

| | **Explained Variance** | **MAE** | **R^2** | **MSE** | **RMSE** |
|---|---|---|---|---|---|
| *Linear Regression* | 0.0705 | 1.1561 | 0.065 | 3.0039 | 1.7332 |
| *LightGBM* | 0.0997 | 1.1223 | 0.0959 | 2.9047 | 1.7043 |

As can be seen in the table XXX, LightGBM again outperformed the statistical learning model according to all of the investigated criteria. Once again, this was to be expected and is in line with the scientific consensus. It is important to note that both models did not perform well and it can be assumed that either regression models are not fit for this type of problem, or that the problem itself is characterized by low explainability, which is often the case when modeling real life issues. It is likely that the main drivers behind the number of days before the flight, when the upgrade is purchased are not measurable, such as how a given day is going for a given customer. Nevertheless the differences between the important variables for LightGBM and linear regression could be interesting and beneficial to explore. Linear and LightGBM regressions findings differ from one another.

**Figure 6. Variable importance for linear regression**

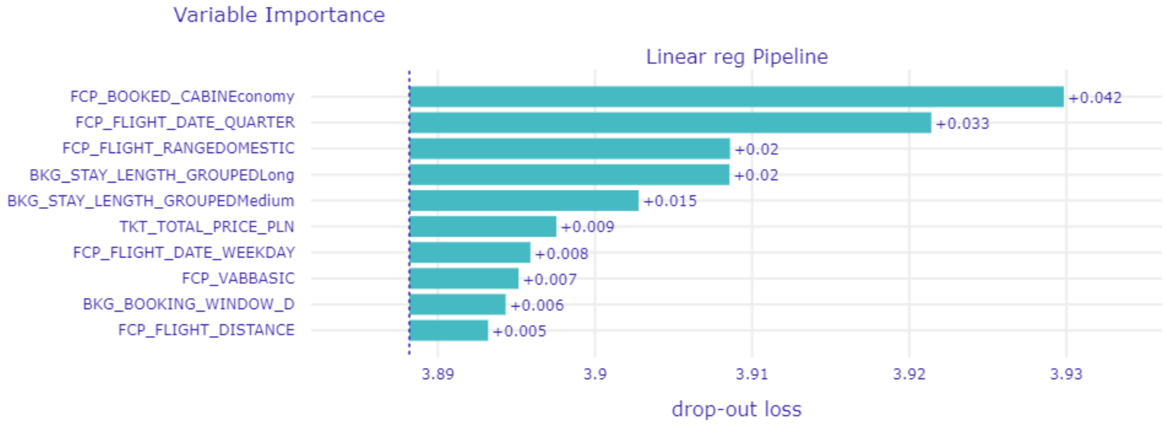
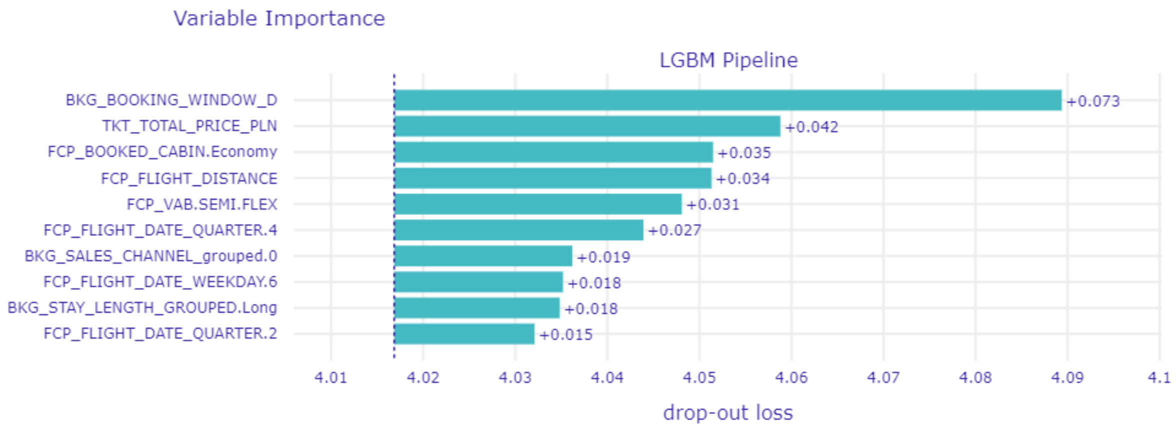



**Figure 7. Variable importance for LightGBM regression**




For the LightGBM The most impactful variable is the booking window, which is not present in the linear regression model. Both of these models agree that some of the prevailing factors in predicting the dependent variable is whether the coupon is for the economy class, whether the coupon has a departure date in the 4th quarter, and how long the passenger will be staying at the place they are traveling to. Interestingly, in the regression problem the distributions of the variable importance are much more similar than in the case of the classification problem. This may be due to the lower number of predictors utilized in the linear regression model compared to the logistic regression.

**Figure 8. Partial-dependence profiles for LightGBM Regressor**

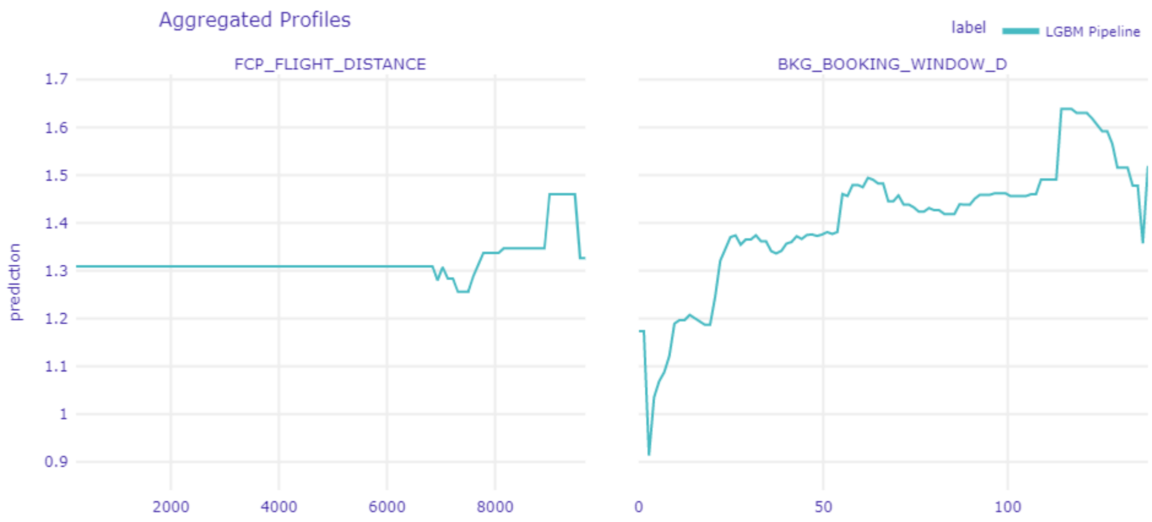
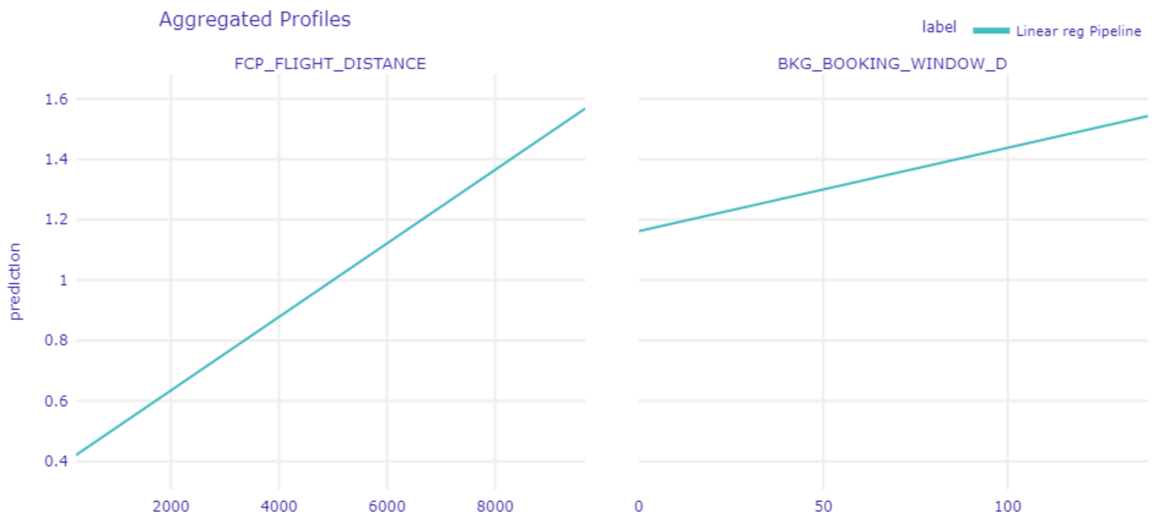



**Figure 9. Partial-dependence profiles for linear regression**




Partial-dependence profiles share similar characteristics in both models. In the LightGBM model, only the long-haul flights tend to significantly influence the propensity score. Whereas in the linear regression there is by default a constant increase in the propensity score with the increase in flight distance, regardless of the interval. Booking window has quite the same interpretation in both models. The longer the time between flight and booking, the better the time for sending a notification to the passenger of available upgrades. It could be due to the fact that the more time the company had, the more opportunities it would have to notify the customer.

## Conclusions and discussion

The use of econometric and machine learning methods can be an immense asset when designing a marketing campaign. In this paper, this opportunity was analyzed and evaluated using the airline class upgrade example, however the results stemming from this paper concern other sectors as well.

Although the explanations of the models provided by blackbox and whitebox models were often quite different, both of them presented often intuitive and sensible reasons for their findings. The LightGBM outperformed econometric methods in both problems, and thanks to the utilization of XAI, one of its main drawbacks, being low explainability was negated. The XAI methods developed and implemented by researchers in recent years may be the final straw when it comes to the ML models finally replacing the econometric ones as the industry standard in most data-intensive sectors. This change may still take some time, as often it is not the lack of willingness of the companies to implement these solutions, but rather the skepticism and relative inflexibility towards them coming from the lawmakers.

During the analysis, it was found that the most important factors when determining the propensity to upgrade a given coupon were the flight distance, the booking window and the price of the ticket. It was also found that other factors such as the number of coupons belonging to a given booking, and the currency with which the coupon was purchased also affect the propensity in a significant way. Additionally, it was found that the time of upgrade prediction is not very promising, as both types of algorithms struggled to produce even a decent model of how this variable behaves. This means that while the binary prediction of upgrade events may be worth pursuing and improving, it is likely that attempts at modeling the time of upgrade are not worth it.

In the future it might be beneficial to perform the analysis of this topic using other algorithms such as Random Forest or Neural Networks, as well as extending the dataset to include information about e.g. extended history of the relationship between the customer and the airline. Furthermore, there is definitely some room left to improve the presented models by extending the range of hyperparameter optimization or choosing different learning objectives.

## References


1. Biecek Przemysław, Burzykowski Tomasz, Explanatory Model Analysis: Explore, Explain, and Examine Predictive Models. With examples in R and Python, Chapman and Hall/CRC, New York, 2021.
2. Fisher Aaron, Cynthia Rudin, Francesca Dominici, All Models Are Wrong, but Many Are Useful: Learning a Variable's Importance by Studying an Entire Class of Prediction Models Simultaneously, *Journal of Machine Learning Research*, 20 (177): 1–81, 2019. Retrieved from http://jmlr.org/papers/v20/18-760.html. Access: 20.03.2022.
3. Hugon-Duprat Cindy, O'Connell John F., The rationale for implementing a premium economy class in the long haul markets - Evidence from the transatlantic market, *Journal of Air Transport Management*, Elsevier, vol. 47(C), 2015, pages 11-19.
4. Jeon Mi-Sun, Lee Jang-Ho, Estimation of willingness-to-pay for premium economy class by type of service, *Journal of Air Transport Management*, vol. 84, 2020, ISSN 0969-6997.
5. Kuo Chung-Wei, Jou Rong-Chang, Willingness to pay for airlines' premium economy class: The perspective of passengers, *Journal of Air Transport Management*, vol. 59, 2017, pages 134-142, ISSN 0969-6997.
6. Matjaž Majnik, Bosnic Zoran, ROC Analysis of Classifiers in Machine Learning: A survey. *Technical report,* vol. MM-1, 2011. Retrieved from https://www.researchgate.net/publication/262170751_ROC_analysis_of_classifiers_in_machine_learning_A_survey. Access: 20.03.2022.
7. Mumbower Stacey, Garrow Laurie, Newman Jeffrey, Investigating airline customers' premium coach seat purchases and implications for optimal pricing strategies, *Transportation Research Part A: Policy and Practice*, vol. 73, 2015, pages 53-69, ISSN 0965-8564.
8. Pesantez-Narvaez J., Guillen M., Alcañiz M., Predicting Motor Insurance Claims Using Telematics Data—XGBoost versus Logistic Regression, *Risks*, vol. 7, 2019. Retrieved from https://doi.org/10.3390/risks7020070. Access: 20.03.2022.
9. Segal Mark R., Machine Learning Benchmarks and Random Forest Regression, UCSF: Center for Bioinformatics and Molecular Biostatistics, 2004. Retrieved from https://escholarship.org/uc/item/35x3v9t4. Access: 20.03.2022.

10. Weinstein Dan, Keller Jeff, Findings from RSG's Bi-Annual Air Passenger Study, Presented at the Choice-based Revenue Management Conference, Georgia Institute of Technology, Atlanta, GA, 2012, page 22.
11. Xu Y, Han D, Huang T, Predicting ICU Mortality in Rheumatic Heart Disease: Comparison of XGBoost and Logistic Regression, *Front Cardiovasc Med*, 2022. Retrieved from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8918628/. Access: 20.03.2022.

# Appendix

**Table 2. Dataset used in analysis**

| VARIABLE | DESCRIPTION |
|---|---|
| **FCP_UPGRADED_FLAG** | Dependent variable in classification models |
| **BKG_SALES_DATE_MONTH** | Month of booking date |
| **BKG_SALES_DATE_WEEKDAY** | Weekday of booking date |
| **BKG_BOOKING_WINDOW_D** | Days between sales date and initial departure date |
| **BKG_STAY_LENGTH_GROUPED** | [Categorical] - Days between first booking departure and last arrival. <0,5> short, (5,14> medium, (>14) long, (one-way) one-way |
| **BKG_FLIGHT_COUPONS** | Number of flight coupons on booking |
| **BKG_SALES_CHANNEL_GROUPED** | Sale channel of booking (LOT channel or external) |
| **BKG_TRIP_TYPE** | Trip Type (Multicity /One way/ Round Trip) |
| **TKT_CURRENCY_FIN** | Payment currency – (PLN/EUR/USD/GBP/SEK/OTHER) |
| **TKT_TOTAL_PRICE_PLN** | Ticket price in PLN |
| **TKT_PAX_TYPE** | Passenger type (Age classification – Adult/Child/Infant) |
| **TKT_CHILD_FLG** | 1 – at least one child on reservation cared by an adult, 0 otherwise |
| **TKT_CORPORATE_CONTRACT_FLG** | Flag indicates corporate trip |
| **TKT_LOYAL_CUSTOMER** | Flag indicates loyalty program member |
| **FCP_FLIGHT_DATE_QUARTER** | Quarter of flight date in local departure timezone |
| **FCP_FLIGHT_DATE_WEEKDAY** | Weekday of flight date in local departure timezone |
| **FCP_FLIGHT_TIME** | [Categorical] - Departure time between: 10 pm and 4 am <22-4>, 4 am and 10 am <4-10>, 10 am and 4 pm <10-16>, 4 pm and 10 pm <16-22> |
| **FCP_FLIGHT_DISTANCE** | Flight distance in kilometers |
| **FCP_FLIGHT_RANGE** | Flight Range (Long-Haul - flight over 5000KM/Short-Haul - flight up to 5000KM/Domestic -flight whithin Poland) |
| **FCP_BOOKED_CABIN** | Booked cabin (Economy/Premium/Business) |
| **FCP_VAB** | Tariff category |
| **EMD_TOTAL_PRICE_PLN** | Total price of additional services on Ticket in PLN |
| **EMD_BAGGAGE** | Flag indicates additional baggage purchase |
| **EMD_SPECIAL_EQUIPMENT** | Flag indicates transport of special equipment purchase |
| **EMD_SEAT_SELECTION** | Flag indicates purchase of seat selection |
| **EMD_PET** | Flag indicates pet transport purchase |
| **EMD_SERVICE** | Flag indicates services purchase |
| **EMD_MEAL** | Flag indicates purchase of selecting meal on board |
| **EMD_FEE** | Flag indicates additional fee payment |
| **RATIO_EMD_TKT_PRICE** | Share of additional services cost in total ticket price |

**Table 3. Number of upgrades depend on aggregation level**

| *Aggregate level* | Upgrades | Number of observations |
|---|---|---|
| *Booking* | 5863 | 2795940 |
| *Coupon* | 8805 | 9224587 |