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Binary Delivery Time Classification and Vehicle's Reallocation Based on Car Variants. SEAT: A Case Study

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Abstract. This note provides a solution to vehicle's compound allocation problem. It has been treated as a classification task employing different Machine Learning (ML) algorithms. It is performed using the known car attributes and the time that vehicles have spent in the compound region, i.e., inventory warehouse, waiting the customer delivery day. Classification results have been assessed with *F1 Score* and *CatBoost* has arisen as the best technique, with values larger than 70%. Finally, reallocation strategy has been tested and outcomes exhibit that company's expert performance is equaled or overcame with respect to time distribution.

Keywords. Machine Learning, Classification, Automotive OEM, F1 Score, Vehicle Reallocation, Anticipatory Shipping, Customer Delivery Time Distribution

1. Introduction

In the last years, automotive Original Equipment Manufacturers (OEMs) are migrating from dealership system to agency model. Both newspapers [1] and consultant companies [2] report about this trend. In this scenario, Machine Learning (ML) can be helpful to automotive OEMs to shipping cars in the region of most likely purchase. This note presents this problem as a binary classification one. The objective consists on **distinguishing whether a car will stay more of less than a threshold days in the compound region, based on the vehicle attributes. Hence, allocate it in the best region**. We prove that ML techniques are helpful to equal and/or improve current delivery time distribution. Compound regions are the equivalent to inventory warehouses managed by the manufacturer.

The article is structured in the following way. Firstly, in Section 2, they are presented related works with the research topic. Hence, Section 3 describes the dataset provided by the automotive OEM source. Next, methodology and results of the research are placed in Section 4 and Section 5,respectively. They are discussed in Section 6. Finally, Section 7 provides conclusions gained and future research paths.

2. Related Works

Mostly of papers focused onto transportation and route optimization. That's why we derived to stock management and product optimization. Reference [3] reviews 49 works

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about planning of capacities and build-to-order production. Afterwards, we find a hub of papers supported by demand forecasting. During 2015, researchers of [4] performed a simulation study of an automaker that operates in Brazil by means of demand forecasting and inventory control of spare parts. Recently, in 2021, the work [5] uses online retailers' clickstream data and historical sales data to explore the optimal quantity and time of products. Other example is developed for Japanese Seru production system. Authors of [6] are capable of optimizing production quantity allocation, right after optimizing worker allocation problem. Finally, authors in [7] found the correlation between inventory volume and sales in the American automobile market.

Later performing the state-of-the-art review, we discovered a gap in the academia. We did not find evidence of a classification system of vehicles in two types of delivery categories. Especially, one based on car attributes and where categorizing the largest quantity of True Positive class, without neglecting the precision, is a key factor. Therefore, we present this research about allocating the vehicles in the compound region more accurate to reduce the customer delivery time.

3. Dataset description

Data involved in this study is supplied by Spanish car manufacturer SEAT. It collects the time spent by each vehicle from an specific car variant in each compound region within the national market from January 2017 to February 2020, both included. Car variant is defined as the combination of Car Model, Equipment Level (TRIM), Order Type, Exterior Color and Engine. Table 1 explains main descriptive values for each compound region and for the totality of the dataset.

Table 1. Main descriptive values for each compound region individually (Region n) and the whole data (Global) collected in the dataset.

	Region 1	**Region 2**	**Region 3**	**Region 4**	**Region 5**	**Region 6**	**Global**
Min [days]	1	1	1	1	1	1	1
Percentile-25 [days]	26	14	16	14	14	18	15
Percentile-50 [days]	46	29	34	27	25	30	29
Percentile-75 [days]	82	71	82	71	62	69	71
Max [days]	716	447	516	490	470	554	716
Number of Variants	1099	2774	1966	2061	2863	2227	4126
Number of Cars	8670	24526	16608	14216	31874	17432	113326

4. Methodology

The first step consists on assigning classes according to different time thresholds, ranging from 1 to 6 weeks. These binary classes are *Fast Delivery* (FD) and *Normal Delivery* (ND). Correspondingly, the weight of FD class in the dataset varies with the threshold and it is shown in Table 2.

Table 2. Weight of FD (*Fast Delivery*) class over the entire dataset according to threshold time.

	7 days	**14 days**	**21 days**	**28 days**	**35 days**	**42 days**
FD cars [%]	5.00	22.67	38.76	48.97	56.05	61.49
FD variants [%]	35.97	65.46	76.30	81.51	84.54	87.03

Secondly, for each threshold, the training process consists on executing cross-validation (5 folds divisions) over data. It is performed under different classification ML algorithms, which are: *Decision Tree*, *Random Forest*, *XGBoost Classifier* and *CatBoost*. This list was defined based on their reliability on other classification problems in the industrial environment [8–10]. With this information, we are able to choose the best algorithm based on *F1 Score*. For the automotive sector, it is relevant to do not only capture as many True Positive as we can, but be precise about the positive class. Papers [11] evidence the employment of this metric in similar contexts.

Afterwards, reallocation step follows for each car variant. In case original region is classified as FD, it is remained. Otherwise, it is headed to all alternative FD destinations. Finally, results are compared with respect to the original situation.

5. Results

Outcomes provided by each ML algorithm can be found in Table 3. The largest values correspond to 28-days threshold. Hence, from this space, *CatBoost* provides the best result. According to Shap values, most relevant features are Order Type and Compound Region.

Table 3. *F1 Score* (%) achieved at each threshold in the cross-validation training process for each ML classification algorithm.

F1 SCORE	**7-days**	**14-days**	**21-days**	**28-days**	**35-days**	**42-days**
Decision Tree	50.05	60.17	69.64	71.13	70.01	68.70
Random Forest	50.43	61.10	70.02	71.32	70.16	68.39
XGBoost	48.74	60.62	71.93	72.75	71.61	69.88
CatBoost	48.72	60.78	72.17	**72.90**	71.77	70.21

Afterwards, we compare the performance of the reallocation step. We measure the delivery time distribution of all new cars headed to each compound region. These numbers are illustrated on Figure 1.

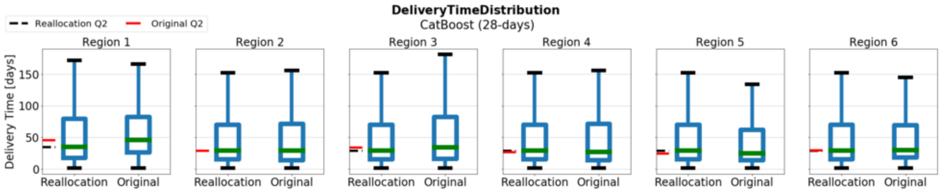

Figure 1. Delivery Time Distribution [days] with and without reallocation for each compound. In each plot of the grid, left boxplot represents Reallocation and right boxplot is Original Delivery Time Distribution. Black dashed line means the median value of the Reallocation Distribution. Red dashdotted line is the median of the Original Distribution.

6. Discussion

From the stage of cross-validation training, the lowest results are given by 7-days threshold for all ML algorithms in Table 3. They reach their peak at the moment of 28-days threshold, when dataset is almost equally balanced (see Table 2). Regarding reallocation stage from Figure 1, Region 1 and Region 3 are the great benefit from this research. Medians in these compounds are lower than the original situation. In the case of Region 5, reallocation median is slightly larger than the benchmark. For the rest of regions, differences cannot be considered as relevant.

7. Conclusions

Although this note does not include criteria to choose between two or more alternative destinations, nor the capacity of them, it proves that ML techniques are helpful to equal and/or improve delivery time distribution of vehicles. They are based on car attributes, such as Car Model, Order Type, Engine, TRIM, etc. The relevance of the task is crucial in the transition to agency model. We suggest that automotive OEMs use them as supportive tool in the decision making of vehicle allocation.

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