Desafio CornerShop

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Expected Outcome:

Predict the `total time` an order placed through the **Cornershop** app will take to optimize the user experience based based on clear and real information delivered through the app according to this indicator.

Model Development:

The entire analysis was developed in `Visual Code Studio` for dissemination and analysis. The code for this challenge was shared via `github` (Restricted access for users with permissions). #Place github link

The code:

The following code installs the necessary libraries for model development. Due to the time for do this challenge, `pycaret` will be used for the model comparison according to R2 and MAE metrics. `Pycaret` is an open-source "low-code" library that allow training multiple models efficiently. This is commonly used for creating "proof of concept models". For more information about it, the following link is attached: https://pycaret.org/

For replicability purposes, "requirements.txt" is attached from python enviroment created for the development of this model. At the same time, you will find a file called "functions.py" which contains all the functions used in this model.

https://s3-us-west-2.amazonaws.com/secure.notion-static.com/72a6877b-c27f-4621-a33c-13175c37641d/requirements.txt

```
#Importar librerias necesarias para el desarrollo del desafio
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
from pycaret.regression import *
from sklearn.model_selection import train_test_split
import gmaps
import os
import random
from geopy.distance import geodesic
from sklearn.linear_model import LinearRegression
import statsmodels.api as sm
from datetime import *

#Lectura de funciones pipeline Cornershop
import cornershop_functions.functions as corner_fx

#Magic commands
%matplotlib inline
!jupyter nbextension enable --py --sys-prefix widgetsnbextension
!jupyter nbextension enable --py --sys-prefix gmaps
```

For model development there are 4 .csv files which contain information related to orders executed in the **Cornershop** app. Once the data is loaded, use is made of the different functions integrated in the algorithm that allow the following to be discussed:

a) Training and testing dataset separation is performed according to indications provided in Readme. For the training dataset (which will be separated later in the training), 8,000 rows are kept leaving 2,000 rows for testing (deliverable).

```
#Lectura de base de ordenes
orders = corner_fx.read_dataset('./data/orders.csv')
print('[INFO]... Mostrando las 5 primeras filas del dataset 😉')
orders.head()
```

```
[INFO]... Leyendo csv con separador ";" 💾
[INFO]... Leyendo csv con otro separador 💾
[INFO]... Mostrando las 5 primeras filas del dataset 😉
```

	order_id	lat	lng	promised_time	on_demand	shopper_id	store_branch_id	total_minutes
0	e750294655c2c7c34d83cc3181c09de4	-33.501675	-70.579369	2019-10-18 20:48:00+00:00	True	e63bc83a1a952fa2b3cc9d558fb943cf	65ded5353c5ee48d0b7d48c591b8f430	67.684264
1	6581174846221cb6c467348e87f57641	-33.440584	-70.556283	2019-10-19 01:00:00+00:00	False	195f9e9d84a4ba9033c4b6a756334d8b	45fbc6d3e05ebd93369ce542e8f2322d	57.060632
2	3a226ea48debc0a7ae9950d5540f2f34	-32.987022	-71.544842	2019-10-19 14:54:00+00:00	True	a5b9ddc0d82e61582fca19ad43dbaacb	07563a3fe3bbe7e3ba84431ad9d055af	NaN
3	7d2ed03fe4966083e74b12694b1669d8	-33.328075	-70.512659	2019-10-18 21:47:00+00:00	True	d0b3f6bf7e249e5ebb8d3129341773a2	f1748d6b0fd9d439f71450117eba2725	52.067742
4	b4b2682d77118155fe4716300ccf7f39	-33.403239	-70.564020	2019-10-19 20:00:00+00:00	False	5c5199ce02f7b77caa9c2590a39ad27d	1f0e3dad99908345f7439f8ffabdffc4	140.724822

b) Using `"corner_fx.estadisticos"` you get basic data of each dataset and using `"corner_fx.unique_values"` you get descriptive information in relation to frequency and frequency accumulated by unique values.

order_products:

1) 198.500 rows and 4 columns.

2) None null values

3) Data on the quantity of products requested is retrieved for each order in **Units** and **Kg**. For products requested by "units", people add **18 prod**ucts in average and an average **2 Kg** in products labeled "**Kg**".

4) The 20 products most requested by customers are which represent 9.3% of the data. It is the table that show that.

Mostrando el top 20 categorias según frecuencia

	Cantidad	Frecuencia	Frecuencia Acumulada
f90b55ea82b8af664f1d7eebb93f25e0	2073	1.044332	1.044332
bdcc4590896a0d0b419d0388fd16a859	1598	0.805038	1.849370
41da609c519d77b29be442f8c1105647	1562	0.786902	2.636272
280cf18baf4311c92aa5a042336587d3	1336	0.673048	3.309320
fb3336fca8851437f980e83045e75749	1092	0.550126	3.859446
42241c8a618f2d925c611ea9faaf44c4	876	0.441310	4.300756
f387d33f0f968f1005e9ef45b66266c6	836	0.421159	4.721914
deeb1b996407d124ff4ddf2f72a96ea0	818	0.412091	5.134005
03c3dafd39fe1c6abeb4bd72e3255d29	799	0.402519	5.536524
7e133b5ec7ad3911f79f03ebf0672200	790	0.397985	5.934509
2b80f98f17cdda9100f8b135f99a090d	755	0.380353	6.314861
d941f7183f6331a2c7d59cf1333e93c6	748	0.376826	6.691688
652cf38361a209088302ba2b8b7f51e0	737	0.371285	7.062972
9559fc73b13fa721a816958488a5b449	732	0.368766	7.431738
9c4a863a146054ac019d6f9167f2354a	704	0.354660	7.786398
1ddf2f2bddd3e706d89fec508c58a69c	699	0.352141	8.138539
1fba6e9254d8a0ae8706eb2560545949	658	0.331486	8.470025
7a123298c12ed5fcefb8b17f6798535f	570	0.287154	8.757179
d9ccf24afa3ef38b3ca9388b6f296682	546	0.275063	9.032242
397c6acfeb22f9e9a1a8764db40d8808	544	0.274055	9.306297

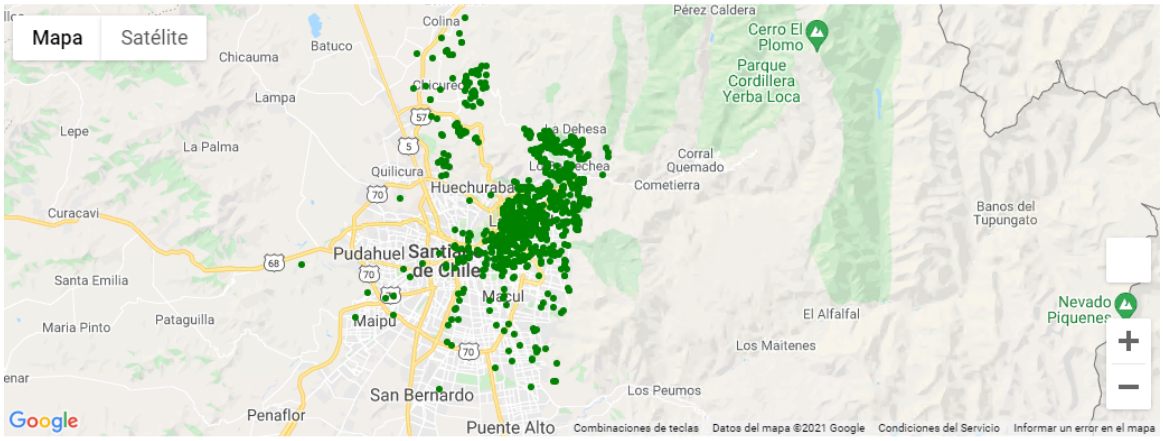
orders:

1) 10.000 rows and 8 columns.

2) No null data. (Only label per construction of the challenge "total_minutes")

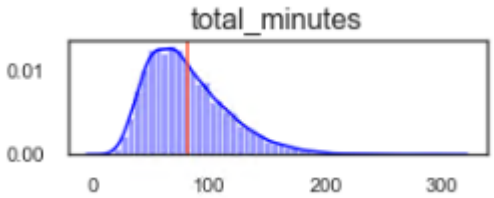
3) Using `google maps API` it is possible to verify that there are orders made in Region Metropolitana, La Serena, Viña del Mar and Concepción.

4) In relation to Region Metropolitana, it can be seen that the orders delivered are concentrated in the central-eastern sector of the capital.




```
[INFO] Frecuencia por dato unico para campo comuna 🚀...

Cantidad de valores unicos por categoría: 115

Mostrando el top 10 categorias según frecuencia
               Cantidad  Frecuencia  Frecuencia Acumulada
Las Condes         2066     25.8250               25.8250
Lo Barnechea       1254     15.6750               41.5000
Vitacura           1042     13.0250               54.5250
Providencia         532      6.6500               61.1750
Ñuñoa               357      4.4625               65.6375
Barrio El Golf      354      4.4250               70.0625
La Reina            284      3.5500               73.6125
Chicureo            279      3.4875               77.1000
Viña del Mar        214      2.6750               79.7750
Santiago            195      2.4375               82.2125
```

5) Orders have an average of 81 minutes. With some edge cases whose total time exceeds 150 minutes.



6) 54.5% of the orders were placed during hours of low demand.

```
[INFO]
Frecuencia por dato unico para campo on_demand 🚀...
       Cantidad  Frecuencia  Frecuencia Acumulada
False      4362      54.525                54.525
True       3638      45.475               100.000
```

7) The two most recurring stores are 1f0e3dad99908345f7439f8ffabdffc4 and 1679091c5a880faf6fb5e6087eb1b2dc which represent 35.28% of the orders in the data.

shoopers:

1) 2.864 rows and 6 columns.

2) The next variables have null values.

```
[INFO]... Cantidad de datos nulos por columna: 🚫

shopper_id         0
seniority          0
found_rate       101
picking_speed      0
accepted_rate     27
rating            84
dtype: int64
```

3) Shoppers on average find 86% of products with an average speed of 2 products per min. It is a base of shoppers with ratings very close to 5, whose 25% percentile is 4.8 and an average of 4.85 points. The historical rate for each shopper is 90%.

4) Given the previous analysis, it is possible to infer that **"picking_speed"** is one of the variables that could be of importance for the prediction. The rest are homogeneously distributed without significant differences.

```
[INFO]... Estadisticos basicos: 🎯

        found_rate  picking_speed  accepted_rate       rating
count  2763.000000    2864.000000    2837.000000  2780.000000
mean      0.861082       1.762392       0.908276     4.848428
std       0.031038       0.665962       0.107911     0.133011
min       0.737300       0.650000       0.240000     3.880000
25%       0.842900       1.290000       0.880000     4.800000
50%       0.863900       1.580000       0.944444     4.880000
75%       0.881950       2.120000       1.000000     4.960000
max       0.971000       7.040000       1.000000     5.000000
```

5) To fill na the missing data, the "seniority" field and the averages related to each metric are used. That is, averages are generated for each "seniority" group and each one of them is imputed in the missing values. This fill can be improved by using interaction of variables related to similar profiles of shoppers.

```
[INFO]... Completando datos vacios en shoppers 👎
[INFO]... Completando datos vacios columna found_rate_fillna: 🎯
[INFO]... Completando datos vacios columna picking_speed_fillna: 🎯
[INFO]... Completando datos vacios columna accepted_rate_fillna: 🎯
[INFO]... Completando datos vacios columna rating_fillna: 🎯
[INFO]... Cantidad nulos: 🚫
shopper_id       0
seniority        0
found_rate       0
picking_speed    0
accepted_rate    0
rating           0
dtype: int64
[INFO]... Mostrando los 5 primeros registros de la base post tratamiento 😉
```

	shopper_id	seniority	found_rate	picking_speed	accepted_rate	rating
0	1fc20b0bdf697ac13dd6a15cbd2fe60a	41dc7c9e385c4d2b6c1f7836973951bf	0.860600	1.94	1.00000	4.870000
1	e1c679ac73a69c01981fdd3c5ab8beda	6c90661e6d2c7579f5ce337c3391dbb9	0.844600	1.23	0.92000	4.920000
2	09d369c66ca86ebeffacb133410c5ee1	6c90661e6d2c7579f5ce337c3391dbb9	0.855900	1.56	1.00000	4.880000
3	db39866e62b95bb04ebb1e470f2d1347	50e13ee63f086c2fe84229348bc91b5b	0.846954	2.41	0.78644	4.843834
4	8efbc238660053b19f00ca431144fdae	6c90661e6d2c7579f5ce337c3391dbb9	0.877000	1.31	0.92000	4.880000

6) It has 4 groups of "seniority" which the first one represent 57.36% of the data.

```
[INFO]
Frecuencia por dato unico para campo seniority 🚀...
                                 Cantidad  Frecuencia  Frecuencia Acumulada
6c90661e6d2c7579f5ce337c3391dbb9      1643   57.367318             57.367318
50e13ee63f086c2fe84229348bc91b5b       719   25.104749             82.472067
41dc7c9e385c4d2b6c1f7836973951bf       440   15.363128             97.835196
bb29b8d0d196b5db5a5350e5e3ae2b1f        62    2.164804            100.000000
```

storebranch:

1) 476 rows and 4 columns.

2) No null data.

3) Latitude and longitude of the different stores are retrieved for the purposes of generating new variables.

Creating Variables:

a) The `geodesic` library is used to measure the distance between the place where the order was requested and the assigned store. With this, a "distance" field is created which gives the Km that exist between both places.

b) The day, month, year, hour and minute of the order are obtained. For analysis and development purposes, "promised_time" is used since the original date of the order does not appear in the dataset. (With this field it could be more exact, avoiding biases and generating optimization analysis for the predictions of each model).

```
[INFO]
Frecuencia por dato unico para campo dia_pedido 🚀...
    Cantidad  Frecuencia  Frecuencia Acumulada
19      5673     70.9125               70.9125
18      2326     29.0750               99.9875
20         1      0.0125              100.0000

[INFO]
Frecuencia por dato unico para campo mes_pedido 🚀...
    Cantidad  Frecuencia  Frecuencia Acumulada
10      8000       100.0                 100.0

[INFO]
Frecuencia por dato unico para campo año_pedido 🚀...
      Cantidad  Frecuencia  Frecuencia Acumulada
2019      8000       100.0                 100.0
```

c) In relation to the previous variables, the dataset only incorporates two days of orders, for October 2019.

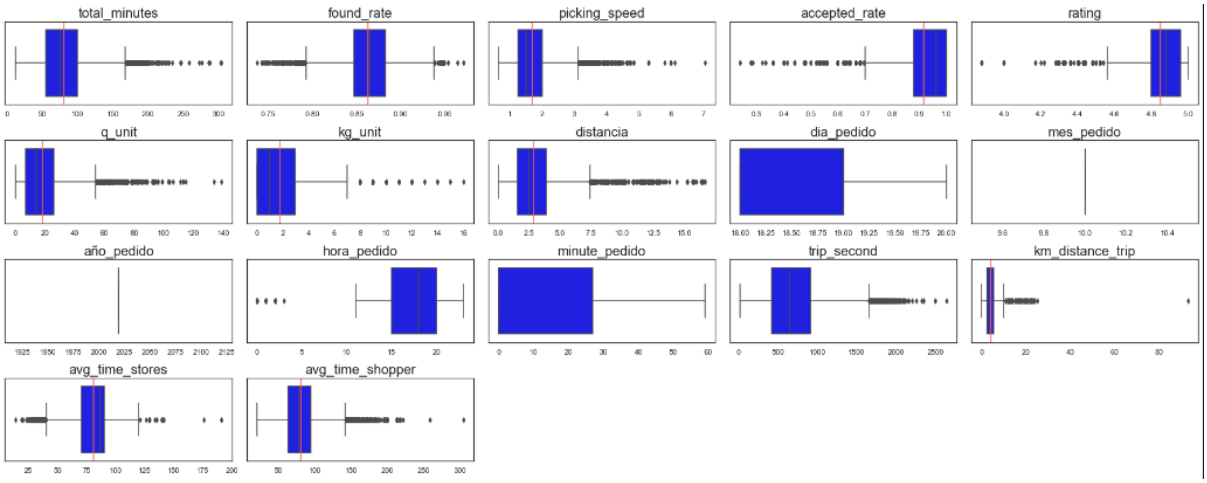
d) By using `Google's API Distance Matrix`, the distance the shopper must travel and the minutes it takes to get from point A to B. Due to the API only allow to get the real time traffic (In present or future), the data was used with updated date and time for investigation purpose. In the case of mounting the model online and that the variable is significant, it can be obtained by consuming the API. To avoid consuming the API, dataset `maps_results.csv` was made available.

e) Through the use of `Google Geocoding API`, "la comuna" from where the order is requested was obtained. This API provides another type of information which for simplicity purposes only this data was obtained. To avoid consuming the API, a dataset `comunas.csv` was made available.

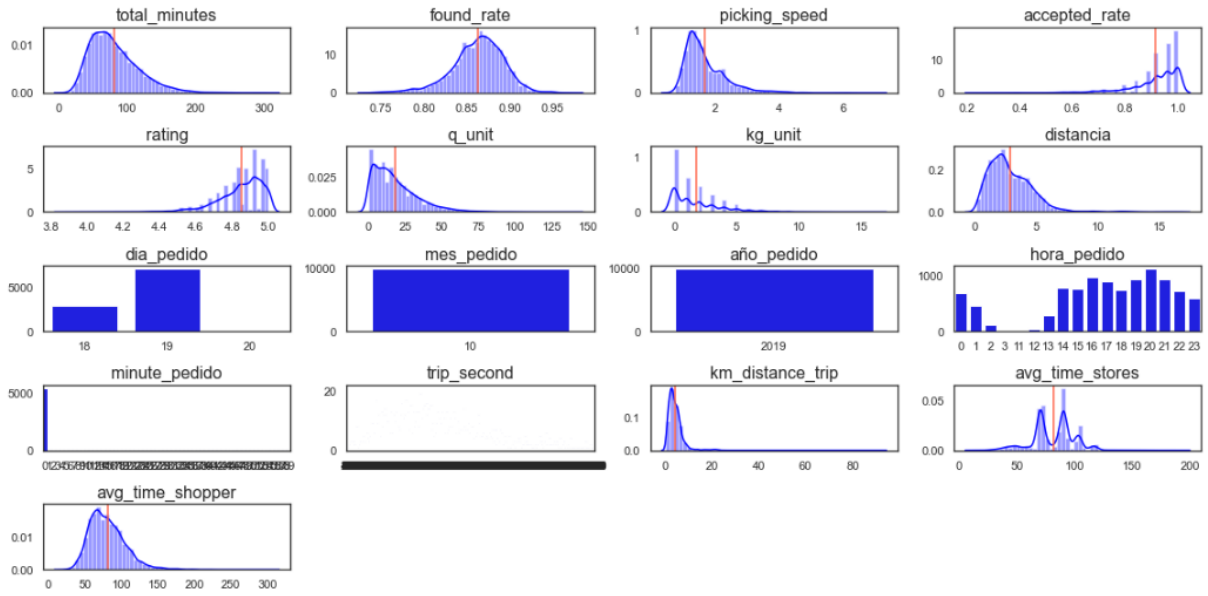
f) It is possible to identify that more than 50% of the orders occur after 4:00 p.m.

```
[INFO] Frecuencia por dato unico para campo hora_pedido 🚀...

Cantidad de valores unicos por categoría: 16

Mostrando el top 10 categorias según frecuencia
    Cantidad  Frecuencia  Frecuencia Acumulada
20       897     11.2125               11.2125
16       772      9.6500               20.8625
21       742      9.2750               30.1375
17       717      8.9625               39.1000
19       716      8.9500               48.0500
14       625      7.8125               55.8625
15       605      7.5625               63.4250
18       598      7.4750               70.9000
22       584      7.3000               78.2000
0        550      6.8750               85.0750
```

g) Once we have the complete dataset, we proceed to apply the `"plot_boxplot"` function to check if the variables have **outliers**. Here it is possible to verify that the delivered data contains a high level of outliers. Considering that there are very few samples to train the model, it is probable that the results in the prediction will not be able to generalize correctly. (Even more so when outliers were removed in training)

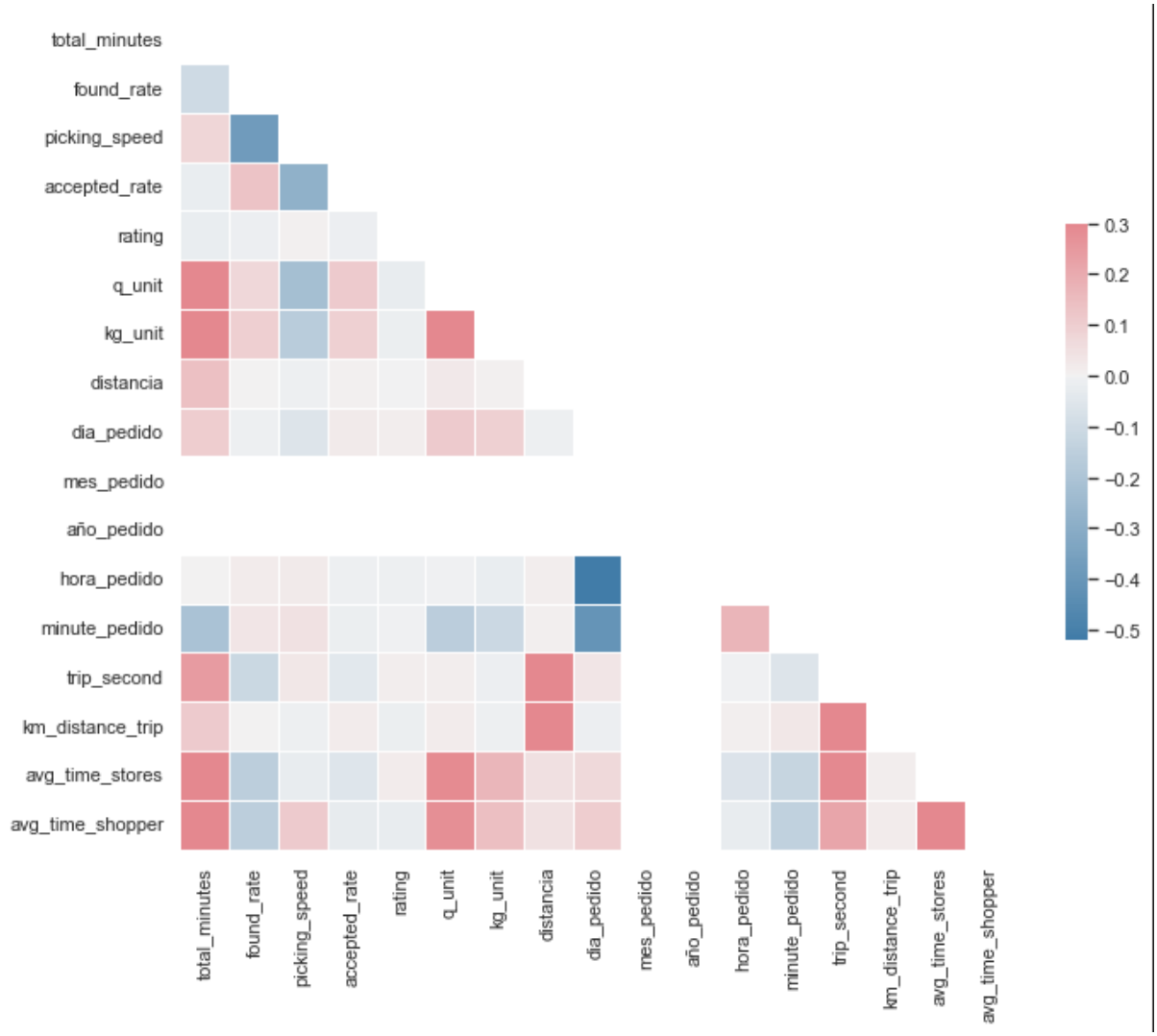


h) With function `"plot_hist_frec"` the distributions are obtained over the total of variables generated. Here it is possible to show variables with data distributed outside the norm.



i) Before training the model, apply `"LabelEncoder"` from sklearn through the function `"cat_encoding"` to convert categorical variables into numeric, keeping their type for training different models.

j) By calculating the correlation between the variables it is possible to see that **found_rate, q_unit, kg_unit, trip_second, distance, minute_pedido, avg_time_stores, avg_time_shopper** are variables correlated with the target variable. In the training process, variables with correlation will be eliminated, maintaining those of greater significance for training.



Entrenamiento del modelo:

The following line of code, configures the necessary parameters for the application of `Pycaret` to our dataset. In this configuration, it is indicated which is the data to be used, which will be the target to be predicted, applying standardization to the variables and specifying which are categorical and which are numerical. For training purposes, `Pycaret` eliminates `outliers` (using inter-quartile ranges), eliminates correlated variables and uses Bayesian optimization of `hyperparameters` to obtain the best `MAE`.

```
print('[INFO]... Configurando pycaret regressor 🎯')
#Aplicacion de Pycaret
model = setup(train_dataset,
        target='total_minutes',
        normalize = True,
        normalize_method = 'zscore',
```

```
        train_size = 0.80,
        categorical_features = cat_list,
        numeric_features = int_list,
        remove_outliers = True,
        outliers_threshold = 0.05,
        remove_multicollinearity = True,
        multicollinearity_threshold = 0.9,
        fold_shuffle = True,
        feature_selection = True,
        feature_selection_threshold = 0.8,
        session_id = 1992)

print('[INFO]... Comparando modelos utilizando pycaret 🆚')
compare_models()
```

`Compare_models()` allows training multiple ML models using Cross-Validation with 10 folds, separating the data into 85% training and 15% for validation. (This configuration was chosen since there is very little data to train).

The result of the process is as follows:

	Model	MAE	MSE	RMSE	R2	RMSLE	MAPE	TT (Sec)
lightgbm	Light Gradient Boosting Machine	14.2698	371.0088	19.2490	0.6963	0.2303	0.1898	0.2300
gbr	Gradient Boosting Regressor	14.5207	384.2778	19.5889	0.6855	0.2365	0.1958	4.8250
lasso	Lasso Regression	14.7277	391.7807	19.7726	0.6797	0.2403	0.2003	0.1560
rf	Random Forest Regressor	14.6488	396.9068	19.9051	0.6754	0.2383	0.1961	5.8340
et	Extra Trees Regressor	14.6412	398.5669	19.9528	0.6738	0.2385	0.1943	9.7280
en	Elastic Net	15.7753	438.3902	20.9144	0.6420	0.2546	0.2197	0.1480
lar	Least Angle Regression	15.3996	443.5119	21.0435	0.6367	0.2516	0.2072	0.7470
br	Bayesian Ridge	13.1069	342.6730	17.5409	0.6227	0.2135	0.1763	11.1620
ridge	Ridge Regression	16.5253	492.8446	22.1855	0.5962	0.2775	0.2220	0.2920
knn	K Neighbors Regressor	17.1738	521.4473	22.8125	0.5742	0.2720	0.2285	2.8610
omp	Orthogonal Matching Pursuit	16.6563	538.7533	23.1882	0.5582	0.2759	0.2228	0.2780
huber	Huber Regressor	17.4353	549.8854	23.4226	0.5499	0.2981	0.2323	11.4520
ada	AdaBoost Regressor	19.7111	585.4970	24.1761	0.5207	0.3276	0.3157	10.0540
par	Passive Aggressive Regressor	19.6433	677.0874	25.9609	0.4465	0.3486	0.2669	0.6260
dt	Decision Tree Regressor	20.5295	774.4844	27.8134	0.3651	0.3305	0.2700	0.2350
llar	Lasso Least Angle Regression	27.5720	1227.2063	35.0022	-0.0017	0.4258	0.4060	0.2550
lr	Linear Regression	951.9050	95878558.9500	7537.9568	-78144.7252	0.9847	13.1460	6.0810

The models are automatically ordered from best to worst performance. However, due to metric purposes, the best model for this dataset is **"Light Gradient Boosting Machine"** with `MAE and R2 score` of **14.23** and **0.84** respectively. Comparing results in validation, an `MAE and R2 score` of **14.26** and **0.7** is obtained respectively, which indicates that the model is not overfitting.

Looking for an improvement in the results, we proceed to apply the function "`tune_model` "of `pycaret`, which optimizes the `hyperparameters` of the chosen model **(lightgbm)** using Bayesian optimization to avoid the `overfitting` of parameters. After applying, the results tend to improve. The following table shows the K-Fold 10 for the training dataset.

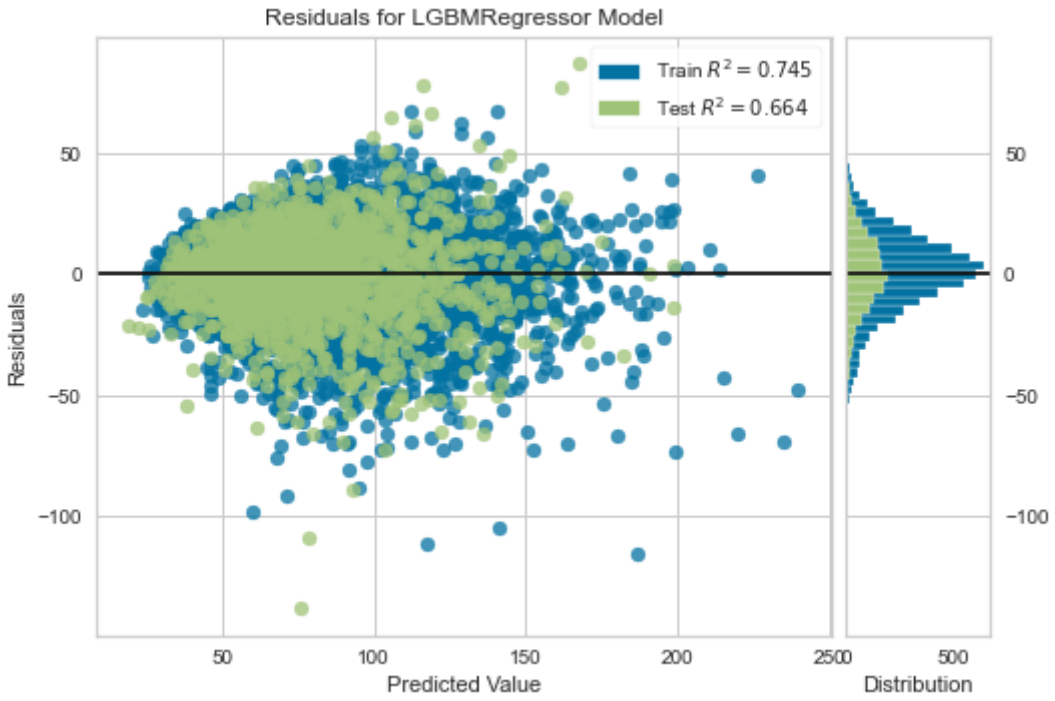
	MAE	MSE	RMSE	R2	RMSLE	MAPE
0	13.5333	328.0151	18.1112	0.7058	0.2194	0.1798
1	14.1196	347.0953	18.6305	0.6953	0.2290	0.1884
2	14.4490	386.7090	19.6649	0.6555	0.2313	0.1919
3	14.0514	362.8475	19.0486	0.7117	0.2233	0.1805
4	15.3749	414.8630	20.3682	0.6800	0.2417	0.2021
5	13.9876	364.1786	19.0835	0.7060	0.2229	0.1847
6	15.3561	405.5957	20.1394	0.6829	0.2440	0.2103
7	14.1435	344.2437	18.5538	0.6811	0.2301	0.1909
8	13.7893	362.5761	19.0414	0.7287	0.2270	0.1801
9	13.8936	393.9643	19.8485	0.7158	0.2341	0.1890
Mean	14.2698	371.0088	19.2490	0.6963	0.2303	0.1898
SD	0.5928	26.8588	0.6963	0.0205	0.0075	0.0094

In order to better understand the output of the model, an optimization function should be used to obtain the actual prediction potential. Using the original date and time of the order, the minutes that the order actually took empirically and the estimated time delivered in the app to the client, it is possible to set up groups to measure the level of accuracy that the model achieves. For example, generating 3 groups: **1) In time:** real delivery time vs estimated < 5 min, **2) Slight delay**: 15 min ≤ real delivery time vs estimated ≥ 5 min, **3) Delay:** Actual vs estimated delivery time > 15 min.

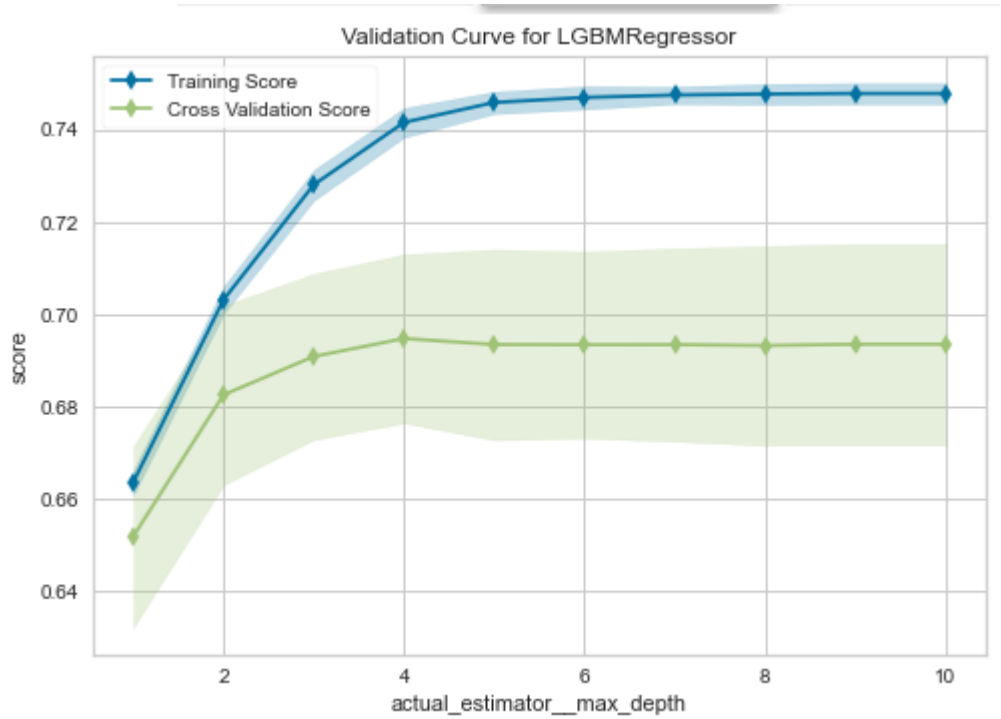
By obtaining the base distribution of these groups, with the new predictions obtained, it could be validated if our new model manages to optimize in time by increasing the `proportion` of cases" In time ", significantly reducing the cases "Delay" and slightly the cases "Slight delay" in order to deliver a rich user experience based on the information provided in the application.

Importance of variables and other graphs (pycaret):

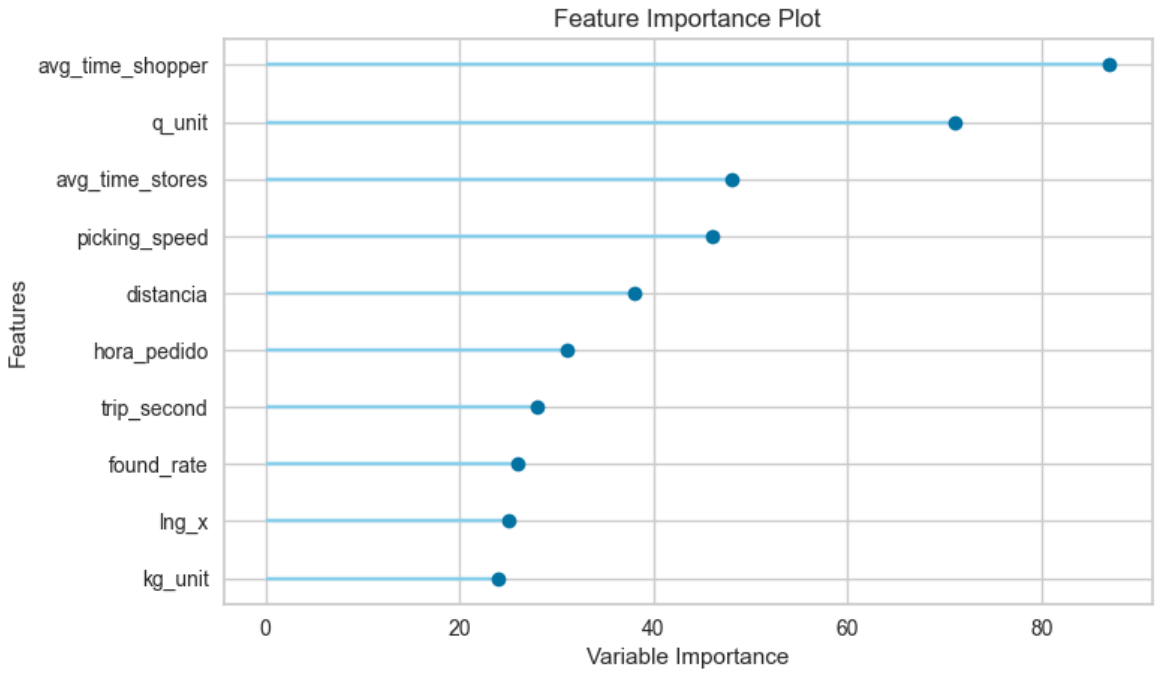
Residuals: The next graph shows how predictions are related to the real value giving their predictions residuals. The target is to closing all the points to 0. It has a normal distribution with mean close to 0 for training and testing.



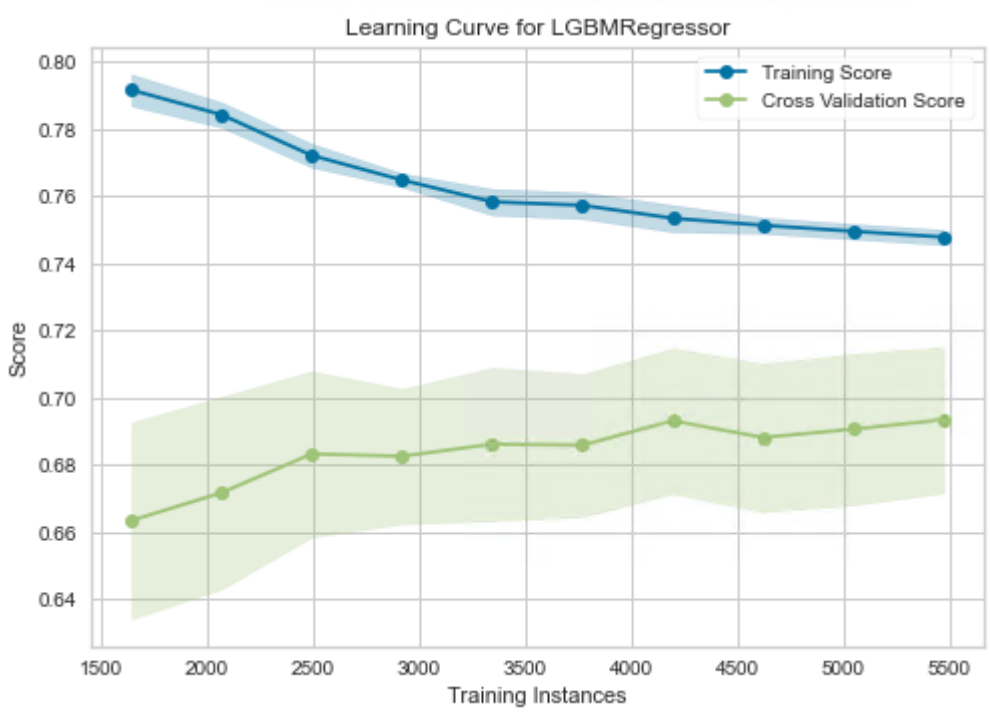
Validation Curve: Allow to check how moving the hyperparameters it could get R2 score for each configuration. In this case, to optimize the metric, max_depth has to be 4.



Feature Importance: Plotting the most significance variables for the model. All of them make sense in specific the avg_time_shopper, picking speed of the shopper, the number of items that the customer add to the order and the distance or trip_second (driving).



Learning Curve: The following graph allows us to know the learning curve of the model used, whose training and testing show very similar results which allow us to indicate that the model is not in overfitting.



Shap Value:

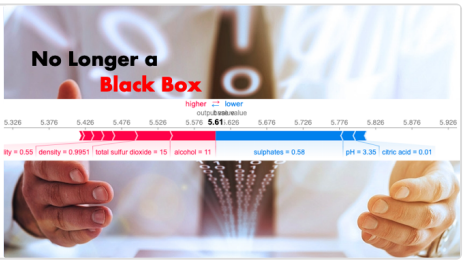
An interesting graph to observe is the attachment. `SHAP value` allows knowing the positive and negative impact on the interaction of each variable with the variable to be predicted. It is a graph that accompanies the importance of variables that allow us to better interpret the reason for the selection of each variable and its predictive power.

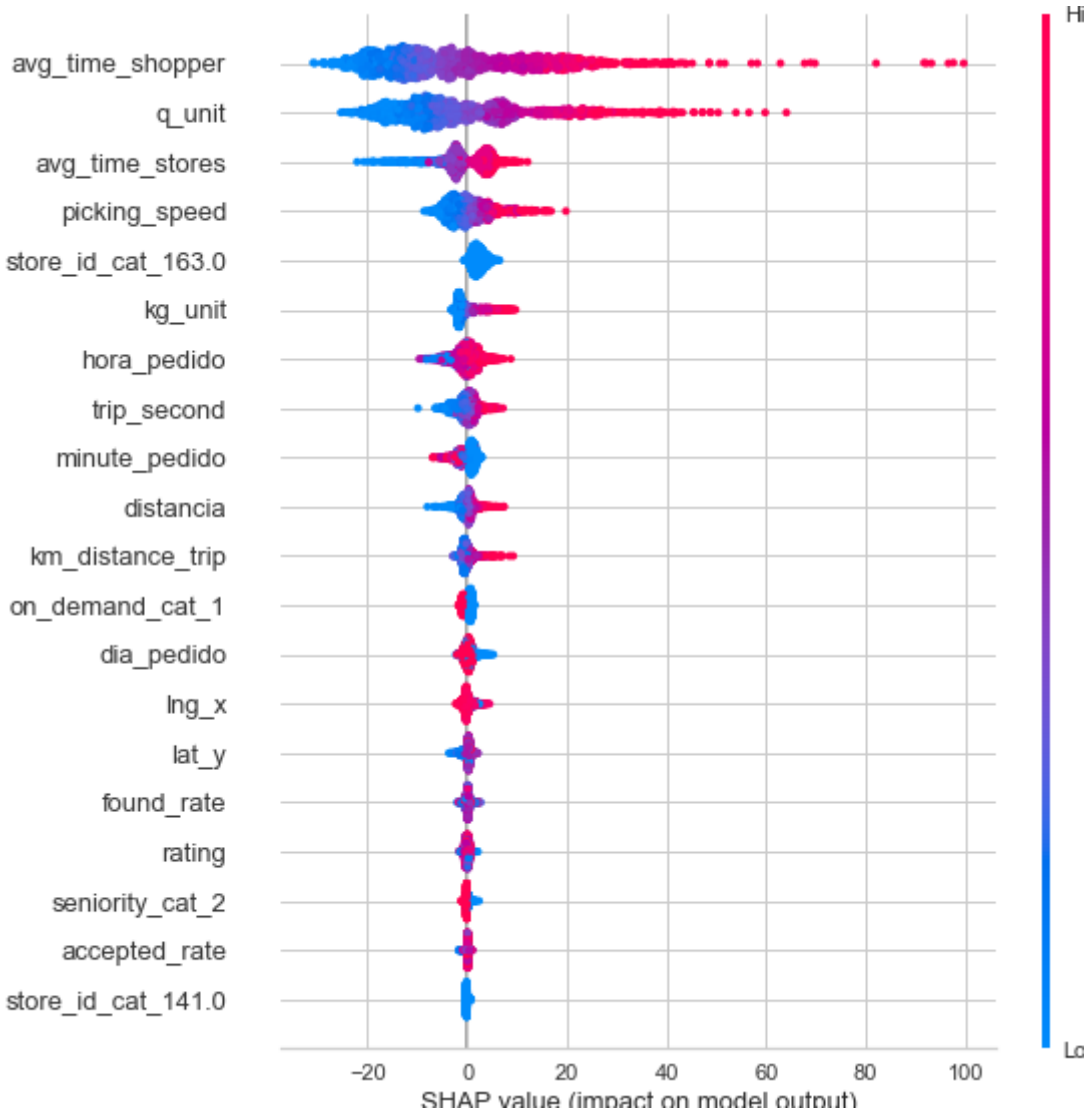
To know more about it, click the next link:

Explain Your Model with the SHAP Values

Better Interpretability Leads to Better Adoption Is your highly-trained model easy to understand? A sophisticated machine learning algorithms usually can produce accurate predictions,

tds https://towardsdatascience.com/explain-your-model-with-the-shap-values-bc36aac4de3d





Model Improvements:

Here are different ways to improve the model:

a) Increasing number of samples: By using more examples, you allow the model to acquire patterns and generalize better during training.

b) Adding New Variables: The variables of the delivered dataset seem not to be enough to improve the predictive power of our model. It is for this reason that it could be retrained with variables such as:

1) Brand and Model of the vehicle where the shopper deliver the order. (Motor's HP)

2) Type of vehicle (Moto, Car, etc)

3) Wheather conditions at the time of the order is entered.

4) Tip for the shopper that the customer put in the order.

5) If the customer lives in buildings or home.

6) More Geographic information

c) Use different methodology: In order to acquire behavioral data, one way to increase predictive power depending on the type of case study is to use `"time series".` Given past events, estimate what will happen in the future.

d) Use feature engineering libraries: Make use of libraries such as `"featuretools"` in order to use `Deep Feature Synthesis` generating x amount of behavior variables that allow increasing the performance of the model.

e) Neural networks: Using `LSTM` recurrent neural networks could be a good way to compare current results and show whether the model improves when using `Deep Learning.`