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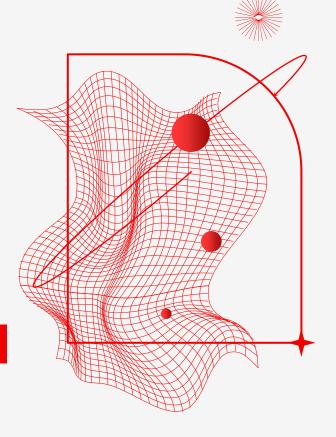






Bussiness Case

What are we looking for?











Rappi's Operations team is interested in decreasing the number of orders that are not taken by any courier, due to the fact that they are not attractive enough for couriers.









Scope



Date time data, measured in one month. September 2017.



Distance from user to store (km), difference in meters between the store and user altitude, total earning, taken as a binary variable: 1 if taken, 0 otherwise.



Identify key drivers that might predict if a given order is taken or not.





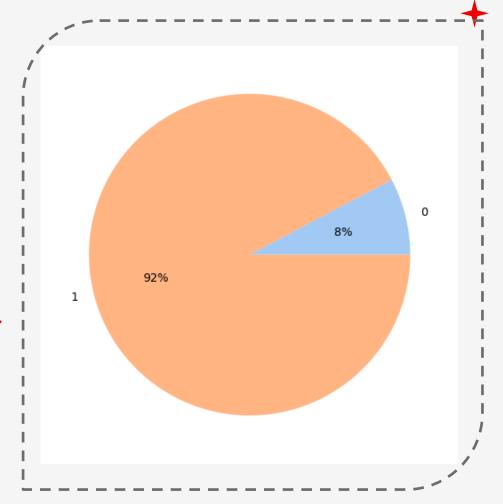




Percentage of non taken orders

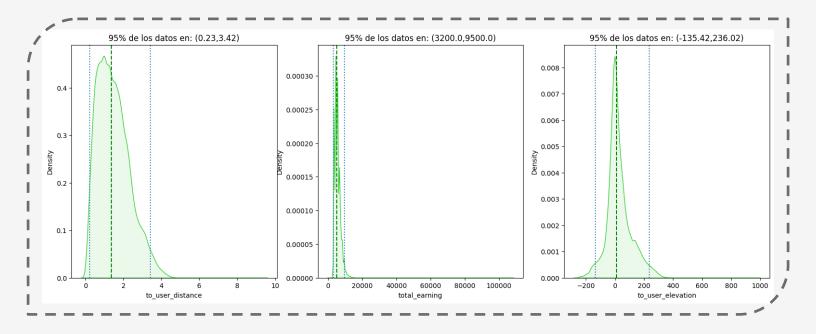
92% of the orders were taken by any Courier, 8% were not taken by any Courier.

Taken (1)	Not taken (0)
115860	9689





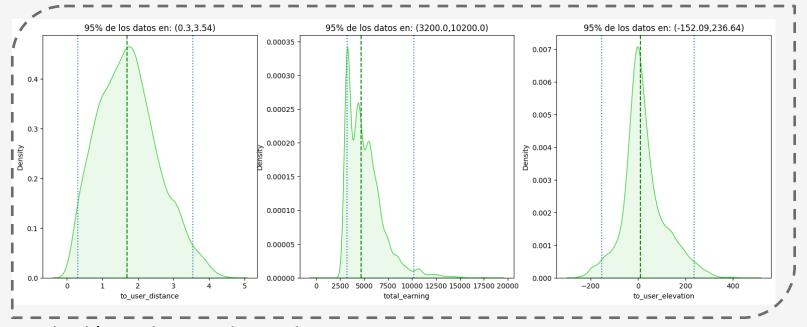




95% of the clients are between 0.23km and 3.42km away from the store. 95% of total earnings of a Courier is between \$3200 and \$9500 95% of user elevation to the store is between -135.42m and 236.02m







Checking only non taken orders:

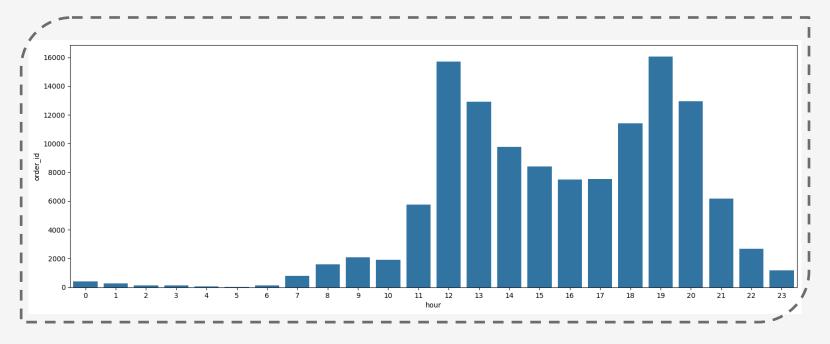
95% of the clients are between 0.3km and 3.54km away from the store.

95% of total earnings of a Courier is between \$3200 and \$10500

95% of user elevation to the store is between -152.09m and 236.64m



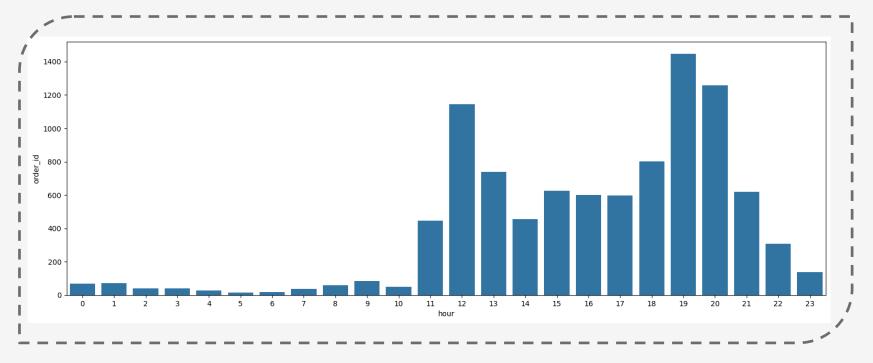




The peak hours in terms of orders created usually matches the lunch time and the dinner time, with steady levels in the afternoon and the early night (around 20 to 21 hours).







Checking only non taken orders, we have critical peaks at the lunchtime and most of the non taken order are concentrated in the late-afternoon – night hours.





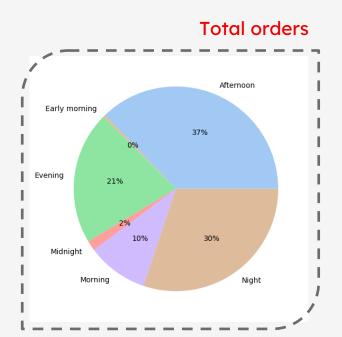
Categorizing the data by hour

If we categorize the hour of the day when the order was originally created, we can gain some general insights among taken and non taken orders.

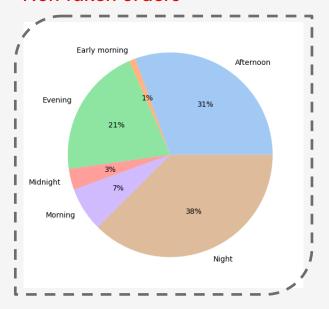
Category	Hours
Early Morning	3 – 6
Morning	7 – 11
Afternoon	12 – 15
Evening	16 – 18
Night	19 – 22
Midnight	23 - 2







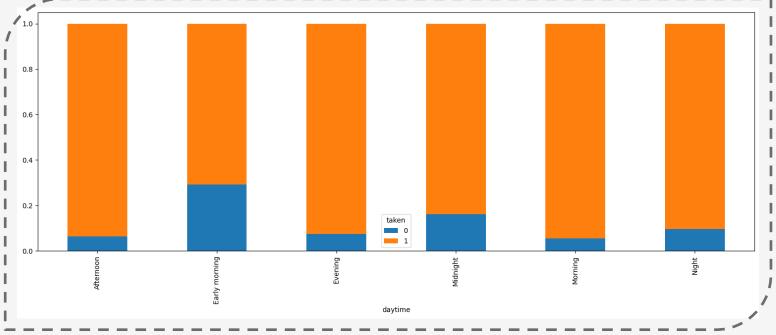
Non taken orders



The highest percentage of non taken orders are in the night



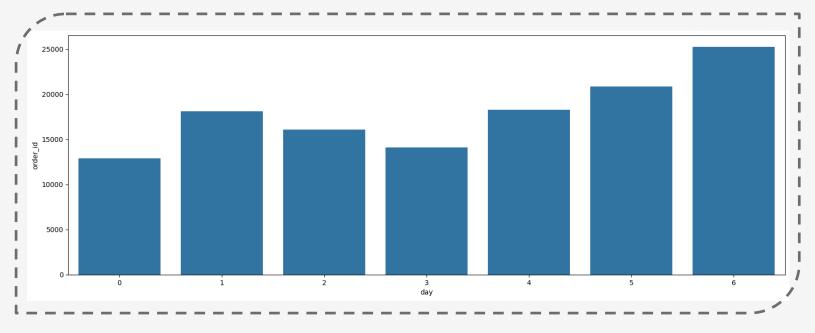




But relatively, in the early morning and in the midnight is more probable that an order may not be accepted by any Courier.



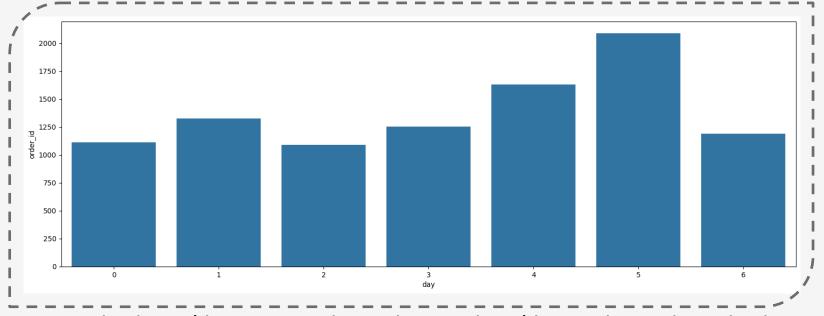




The days that have most orders are on the weekends (Friday, Saturday and Sunday) and the Tuesday.



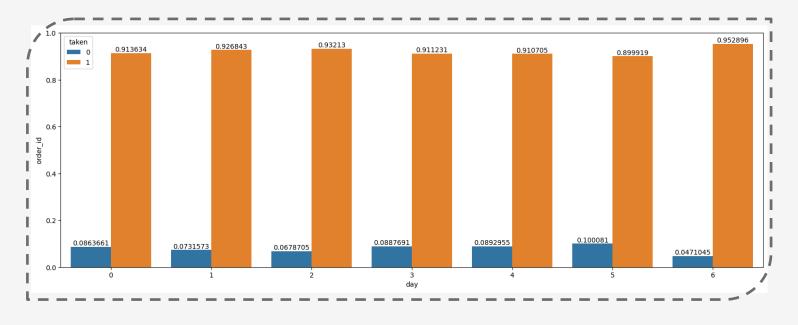




But the days with more non taken orders are the Fridays and Saturdays. The day with less non taken orders is Sunday.







The day with highest percentage of non taken orders is Saturday (10%) and the day with lowest percentage of non taken orders is Sunday (4.7%)

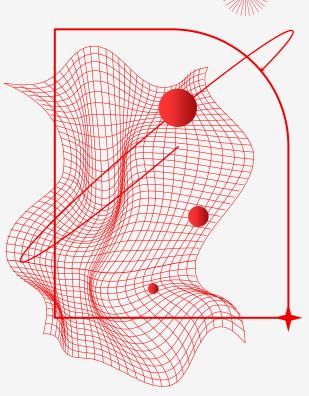






Prior Analysis

Possible patterns in the data





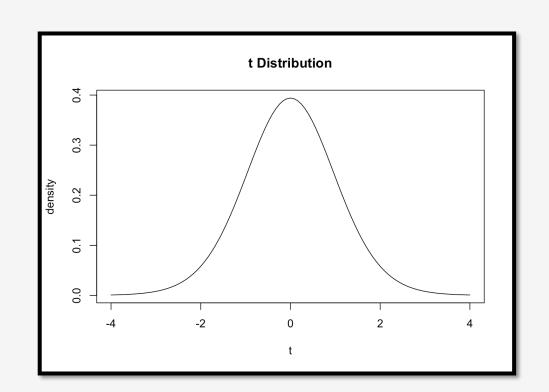


T-test



We test for mean differences with the null hypothesis that the taken orders have lesser values that the non taken orders.

We assume different variances for each group for robustness.







T-test for difference of means



The total
earnings is
higher in the
'taken' group.
P-value = 2.3e-55

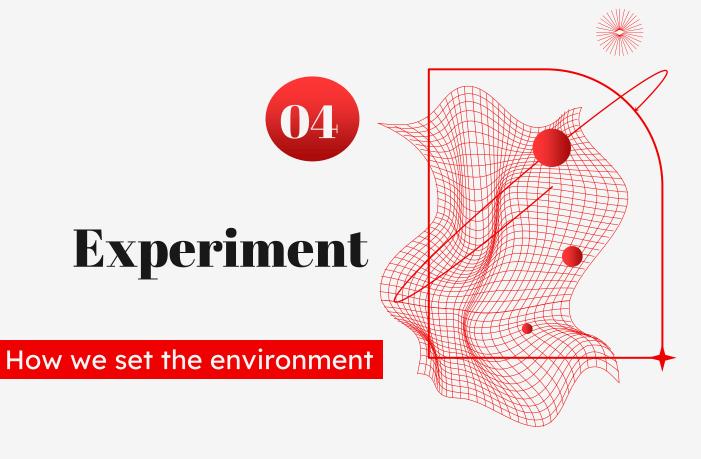


The total distance is lower in the 'taken' group.
P-value = 1



The difference in altitude is positive and higher in the 'taken' group P-value = 1.1e-5

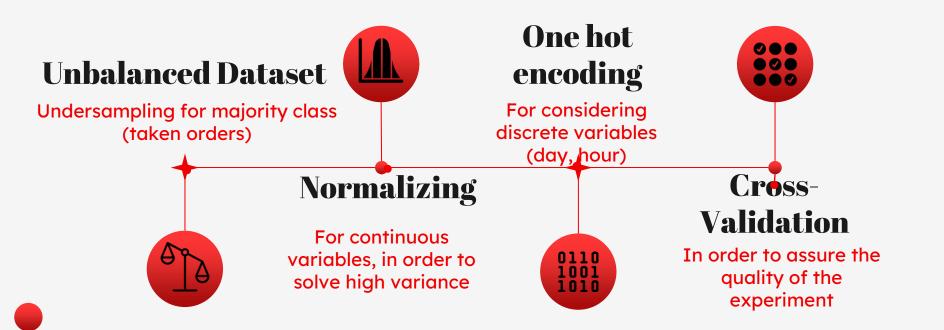






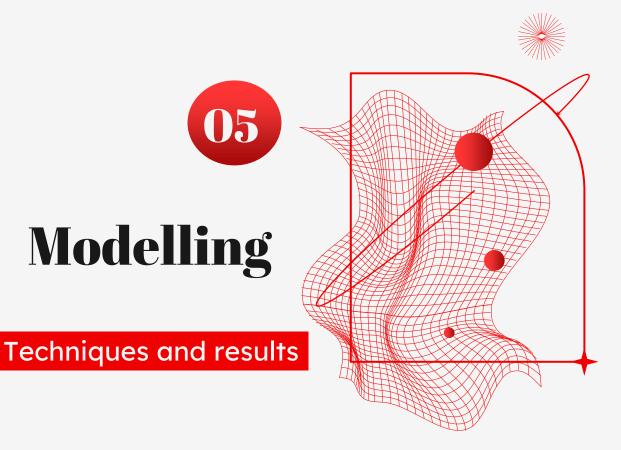


















Modelling Results

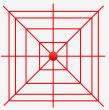
Types of classification models tested: 3 of them ensembles, logistic regression, Naïve Bayes, SVC.

Different configurations of parameters, with 3 validation folds.

Different metrics of classification: accuracy, f1, precision, recall and ROC - AUC

Highly relevant variables capable of giving valuable insights







XGBoost

Got the highest score! 0.66 average in the train and test split across all metrics!

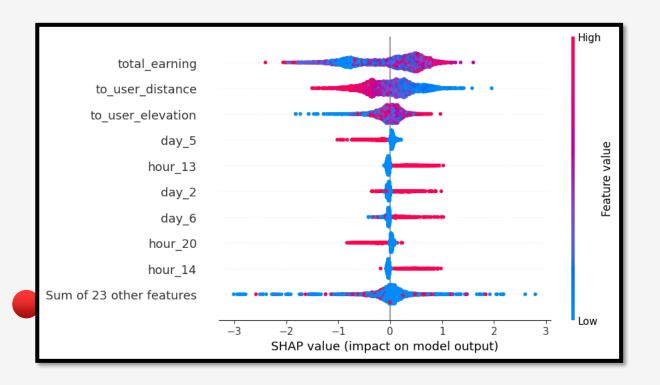








Variable Interpretation

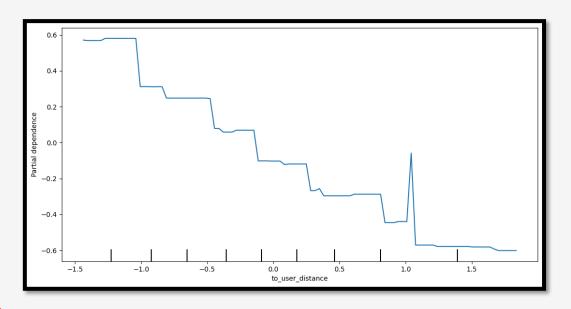


SHAP values strongly suggest that the 20 hour and the Saturday are strong predictors whenever an order is not accepted. Higher total earning and lower user distance are strong predictors of higher acceptance.





Partial Dependence

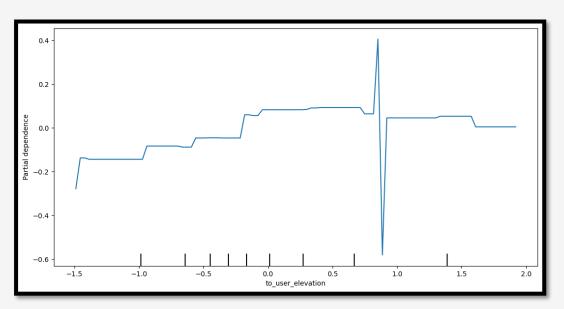


Partial dependence shows the interaction of the variable (x-axis) in the response (y-axis). The greater the user distance, the less likely it is that a courier will take the order. The interpretation is based on the basis or average of data points.





Partial Dependence

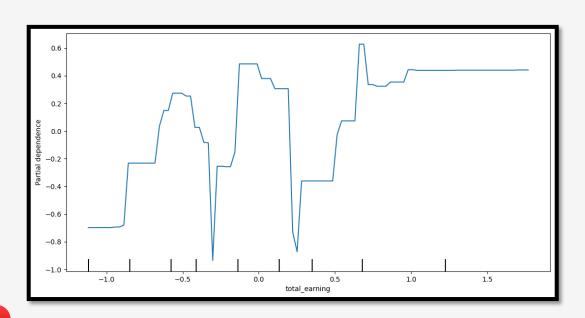


In this case, the lower the user elevation, the less likely is that a courier will take the order. It stabilizes after the average of datapoints.





Partial Dependence



The total earning of the courier has a direct relation on the decision of taking or not an order. It stabilizes after one std. deviation over the average.







Final conclusions and remarks







Key Hours

Offer higher rates at night to the couriers



Rates for distance

Offer differential rates based on the distance to the user



Happy Weekdays

Offer incentives to pick more orders on saturdays



Lunch hours

Encourage the user to order before peak hours to avoid saturation in the lunch and dinner hour



Weather checking

For an upcoming challenge, take into account the weather information





EXTRA: Weather info

Average temperature in Celsius degrees of the localizations, at 11:15, 14 December.



Meter/sec average wind speed on the localizations





Visibility for all locations, no fog detected today!



Thank you!

