Better prediction, more customer engagement

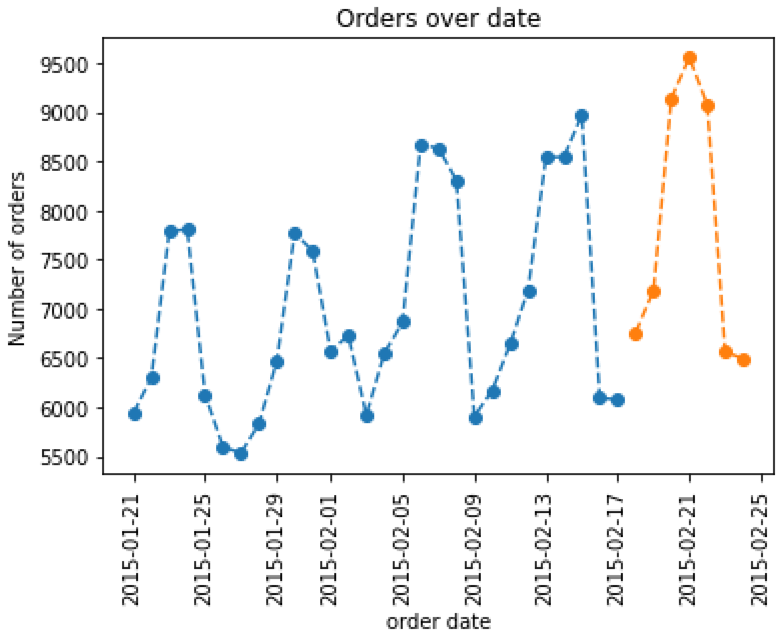
Goal: predict delivery time in order to increase the customer experience

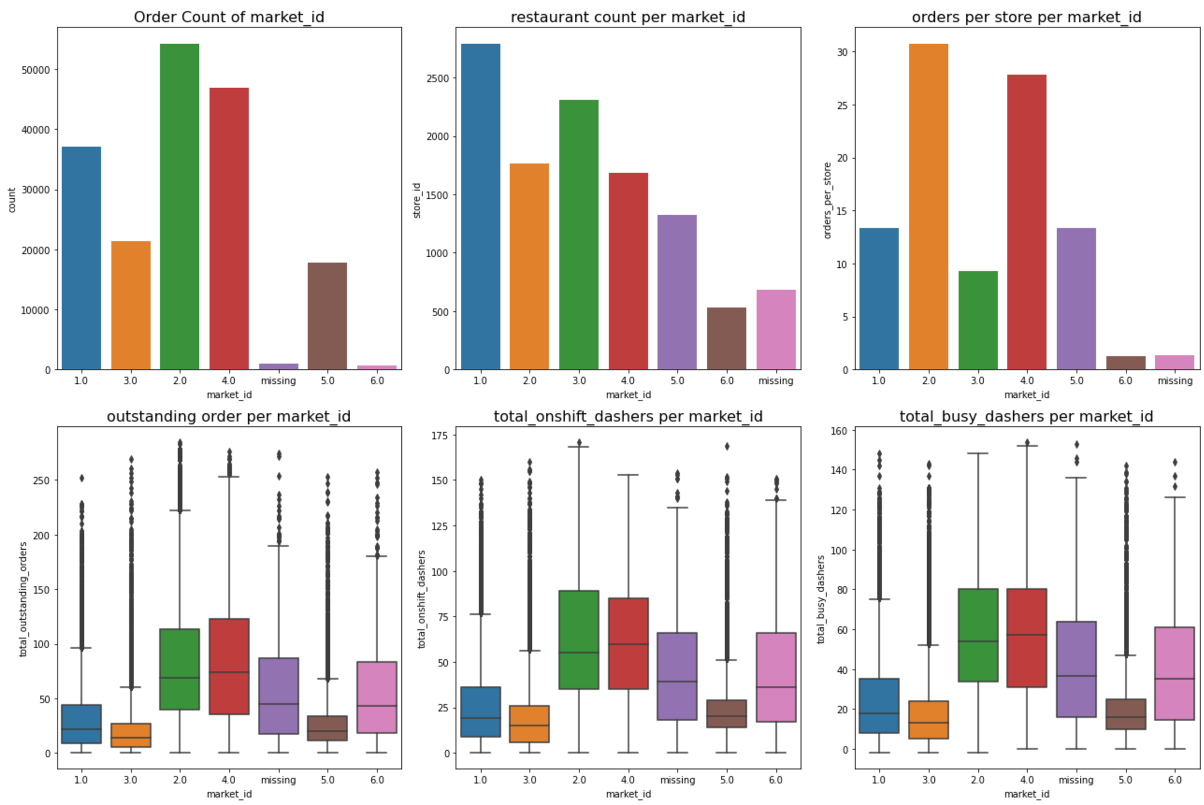
(A) Business summary:

Data analysis:

The overall trend is in progress and there is a weekly a pattern.

Fri and Sat are the highest peak but 2/16 is a holiday therefore 2/15 is still at a high peak.





based on the plot above,

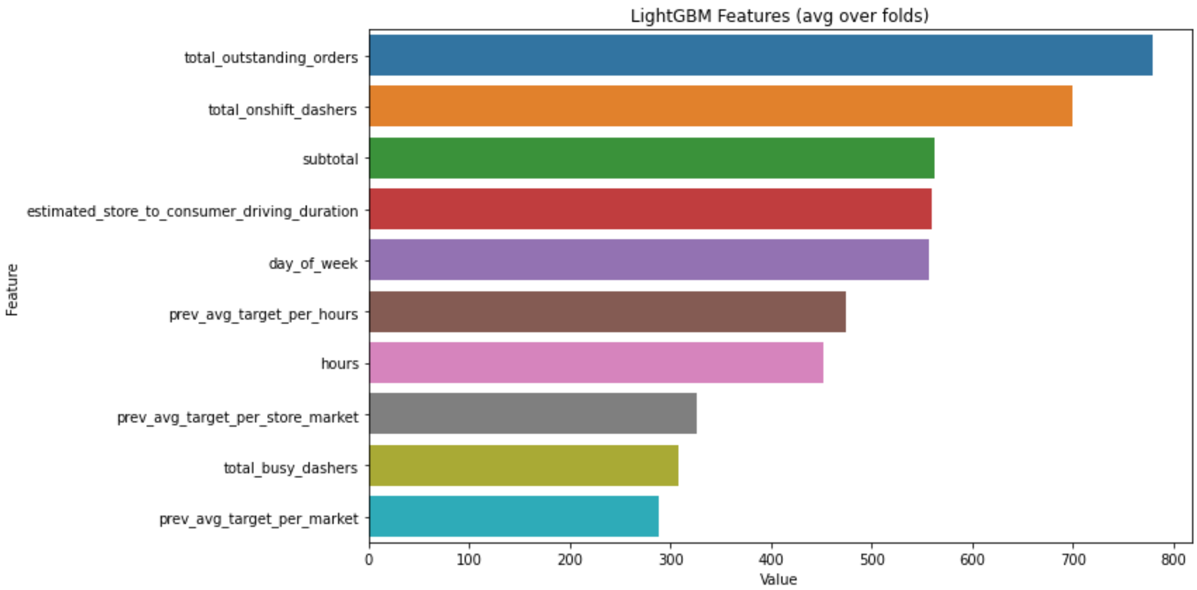
dasher side:

(a) market 2,4 are the top two markets which have large volumes of orders ,and both of them also have the highest average busy dasher,onshift dasher and outstanding orders. good news the demand is strong but it also means there is a problem in staffing, we should provide incentive to the dasher to work during the busy time.

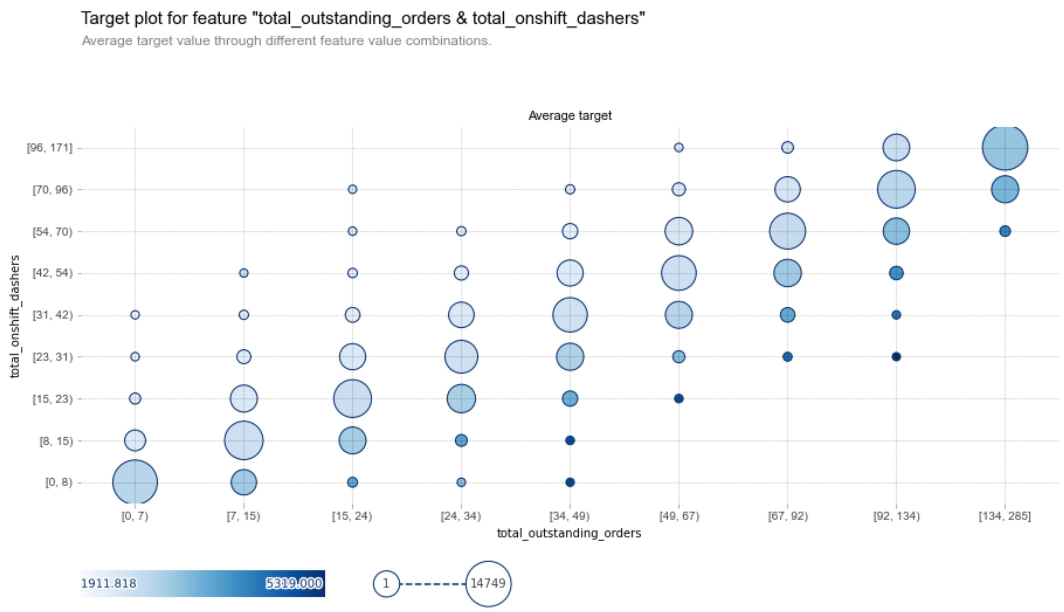
(b) for market 1, we can see there is some space for order growth and averagely, one store receives the highest orders among these markets. It means we should (1).do more marketing in this market to acquire more customers (2).recruit more merchants and share with them this is good timing for stores to join the doordash merchant community. Once the order demands goes up, it’s time for dasher’s growth

Modeling:

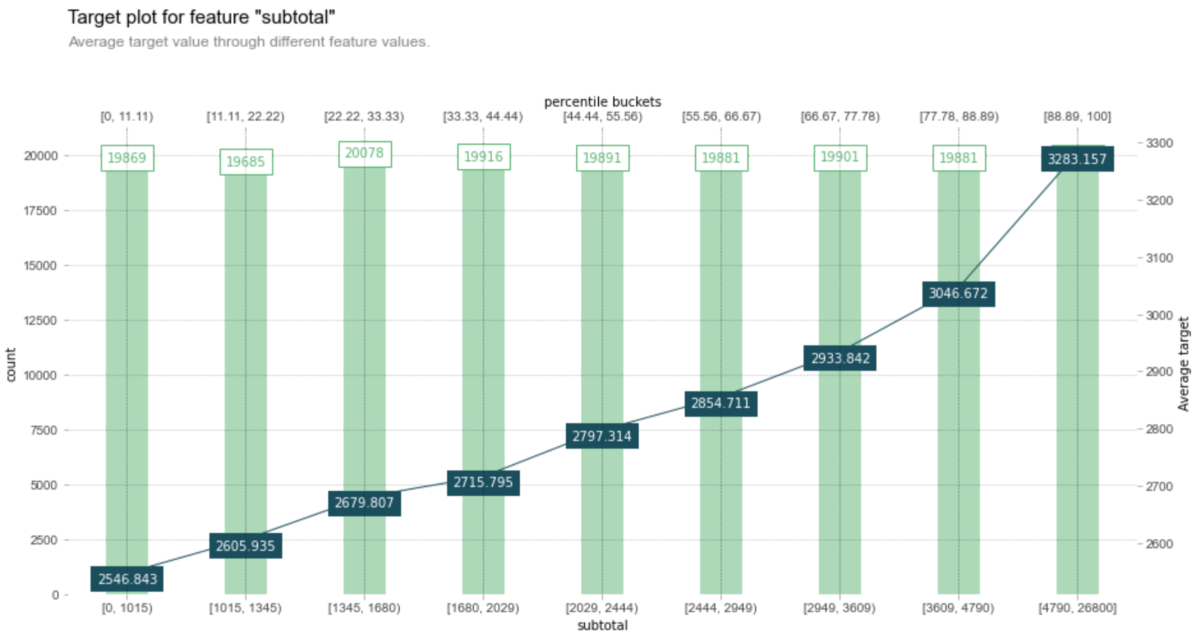
From the modeling side, we can see the top 3 of the most influential features.



Total_outstading_orders and total_onshift_dashers are the top two features drivin the model prediction.

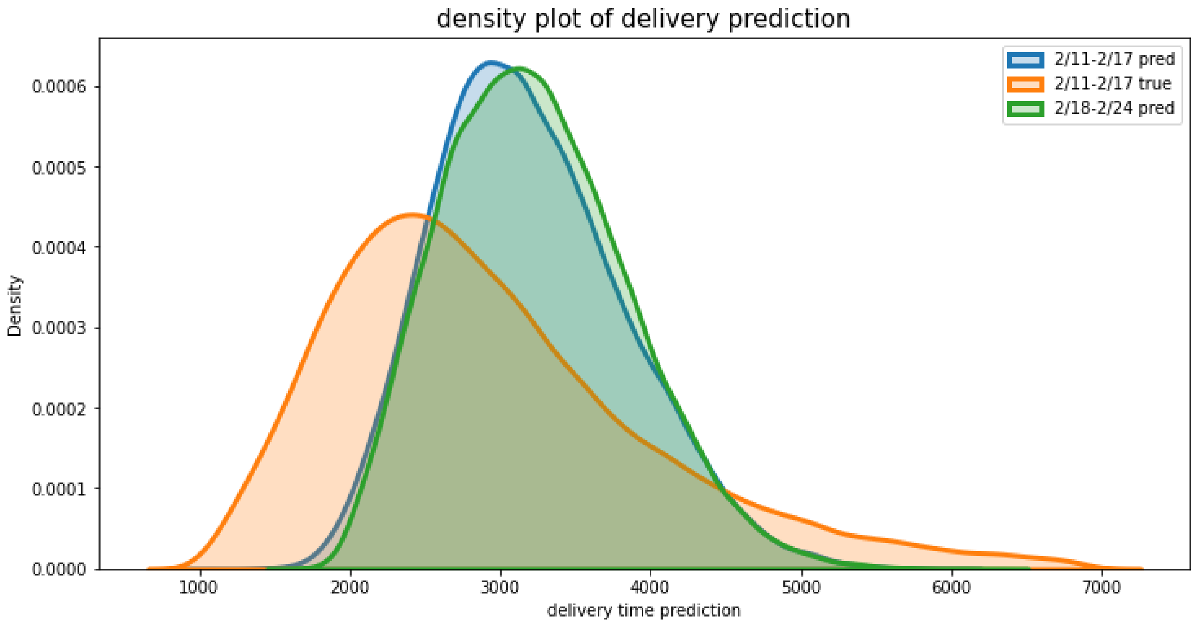


From the plot above we can see the orders are most concentrated on total_outstanding_orders / total_onshift_dashers =1, ratio > 1 , the delivery duration will be longer; ratio < 1   the delivery duration will be shorter which makes sense. usually dashers.



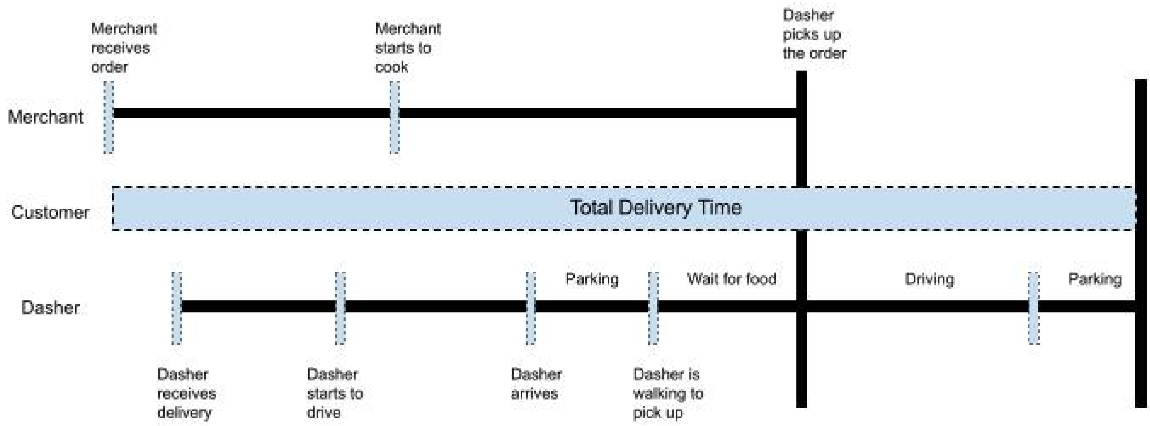
Based on the plot above, we can see if the subtotal is higher the delivery duration is longer. subtotal is higher which means the customers order more items or more fancy food which could take more time to prepare.

Model Prediction QA:



We can see all 2/11-2/17 predictions shift to the right compared to true data, this is due to the business requirements that we prefer overpredict rather than underpredict.
Based on the plot ‘orders over date’, we can see the last week (test data), the orders volume is in an increasing trend, therefore 2/18 prediction is slightly higher than 2/11-2/17 prediction.

(B) In the modeling process I believe adding the following features would be helpful:



Based on the plot above, I believe the current features provided by the datasets doesn't fully capture the whole journey of total delivery time.

1. cuisine category. Once we know which type of cuisine is popular now, we can better understand the trend and we can try to acquire more merchants which provide the cuisine in demand. At the same time other types of cuisine which are not popular but delivery is usually on time ,we can promote it.
2. How does this order get placed? DoorDash can send the orders through fax, email, tablet, or direct point of sale integration in some cases. Once we know a certain type of protocol usually delivers on time we can try to promote this more. On the other hand, if other types of protocol usually have late delivery, we need to figure out why.
3. total items. Currently we only know the subtotal but we don't know how many items. Once we know the total items, we can somewhat know if it's a fancy restaurant or not. At the same time, we also know how big is the size of this order that the dasher needs to handle. Usually dasher will spend more time picking up the large(item count) order.
4. cooking preparation time estimate. It's one of the longest waits in the whole waiting period. and it also shows the current loading of this restaurant. If we also know the estimated drive time to the merchant, it helps us better understand late delivery is due to the dasher or the merchant. Otherwise, the customer probably gives a bad rating to the dasher, we will never know it's due to the merchant.
5. average parking time from previous X weeks. For some areas, finding a parking space may take up to 20 minutes.

Moreover, the details of customers, merchants and dashers would be valuable if we would like to segmentize and apply it to marketing promotion and recommendation.

(C) Model proof of concept.

1. We need to clearly know why we need a new model and what the business problem is.
Scenario : We believe if we increase the accuracy(any customized metrics) of prediction by X%, the customer lifetime value will increase by Y% .

Once we know if the estimated extra revenue from CLTV increases > (the model development/production/maintenance cost + risk of bug). It means we should really move forward.

2. Who is the decision maker? CEO or CTO. I will try to translate the metric in the way they really care and understand. eg. the increase in revenue/ROI or customer lifetime value.

3. We can do a backtesting using historical data and compare the metrics for the first try. If it shows a significant improvement based on the business goal I mentioned previously,
we should start to run A/B test (expensive)

   a. traditional A/B we can pick two cities or metro areas which are isolated from each other and conduct AA tests to make sure these two cities are similar enough. Once the AA test passes we can conduct the A/B test. The difference in average CLTV in the treatment(using the new model) group before and after treatment minus the difference in average CLTV in the control group before and after treatment..By comparing the relationship between the treatment markets and control markets before the new model launch, we can obtain an appropriate counterfactual to estimate a causal effect of the new model.
   b. Learned from doordash conference, we can conduct switchbak testing and make the splits based on region-hour unit
      Once randomization happens on the region-time unit level, each delivery is bucketed into to a treatment or control group based on that of its region and time
      we can compare the customer experience(eg. CLTV) between the control region-hour bucket and treatment region-hour bucket