Didi delivery estimate

With the Mission Make eat well without effort, every day, for everyone, one of our top priorities in Uber Eats is ensuring reliability. We need delivery partners to arrive at the restaurant once the food is ready, where time forecasts always play a critical role across the order life cycle. The Uber Eats delivery system is launched with an algorithm that matches greed, and by using a globally powered algorithm that time forecasts can be more efficient. Uber's in-house machine learning platform, Michelangelo, has provided great assistance in facilitating the overall process for data scientists and engineers to solve machine learning problems. Our biggest challenge of lack of soil permission in the O2O business model has been addressed by concluding label data through feature engineering work and harnessing feedback loops to retraining models. Estimated delivery time forecast models are designed to be flexible enough to handle multiple scenarios due to the uniqueness of newly accessed information in different stages. Uber Eats has become one of the fastest growing food delivery services since the initial launch in Toronto in December 2015. Currently, it is available in over 600 cities worldwide, serving more than 220,000 restaurant partners and has reached 8 billion gross bookings in 2018. The ability to accurately predict delivery times is greatest for customer satisfaction and retention. In addition, time forecasts are important on the part of supply as we calculate the time to send shipping partners. My talk recently covered how Uber Eats has leveraged machine learning to address these challenges. Machine learning at Uber Eats With Make missions eat well without effort, every day, for everyone one of our priorities is ensuring reliability. First, we need to set the right expectations by providing an accurate estimate of delivery time to avoid disappointment in case of delays. Next, we need to calculate the perfect time to send delivery partners to consume food. Ideally, they are supposed to arrive at the restaurant as soon as the food is ready. By arriving too early, they will take the parking lot of the restaurant and the dining area. On the other hand, arriving late will lead to the cooling of unprofitable food. Therefore, time forecasts always play a critical role across the order life cycle, which is reflected in the figure below. Time forecasts through order lifecycles there is no other way to ensure accuracy without using machine learning technology. However, challenges arise along the way with its core development. Compared to other machine learning problems, challenges we are a lack of land authorization data, which is pretty common in online-to-offline business (O2O) models. However, it is the most critical component of machine learning, as we all know the rubbish comes in, rubbish comes out. Another is the uniqueness of Uber Eats as a three-sided market (delivery partners, restaurants, and eaters), which makes it to take into account all partners for each decision we make. Fortunately, Uber's internal machine learning platform - Michelangelo has provided great assistance in facilitating the overall process for data scientists and engineers to solve machine learning problems. It provides generic solutions for data collection, feature engineering, modelling, serving both offline and online predictions, etc., which saves a lot of time compared to reinventing the wheel. Michelangelo - The above online and offline predictions provide an overview of the online and offline forecast pipelines. The online section is primarily for making predictions with real-time and near real-time data collected through Kafka and processed by streaming engines such as Samza, Flink, etc. Ultimately, they will continue in Cassandra's feature stores. For the offline section, data collected from different sources will be processed over-pre-processed by SparkSQL and continuously in HIVE feature stores. Then we will train models based on the algorithm provided by the platform, which supports everything in Spark MLlib, some deep learning models, etc. Feature reports - distribution of each feature and importance to model This is a feature report for a trained model. It provides a lot of detailed information such as data distribution and feature importance, which is very useful for feature engineering work. How time power forecast transmission system Now let's find out how our shipping system works and has evolved through time forecasts. From a high level, it is clear that the transmission system is the brain of the Eats business. The goal is to decide on the most optimal demand and supply matching. In our context, demand is ordering and edialant supplies are shipping partners. As we mentioned earlier, time is key because we need to make sure delivery partners will arrive at the restaurant as soon as food is ready to be picked up. There is no doubt that we have multiple effects before reaching the current level. To help people understand the impact level, comparisons between before and after introducing time forecasts to decide on delivery times are provided below. We started with fixed values that are guessed to decide when to send delivery partners to pick up food. For example, if the eater places an order at 5:30 p.m., we assume the food takes 25 minutes to prepare and the delivery partner needs 5 minutes to reach the restaurant, so we will start shipping at 5:50 p.m. Apparently, it is not scientific to use 25 minutes for all orders from the restaurant regardless of whether the dish ordered 1 serving or 10 servings the same goes for a 5-minute designation for all delivery partner's journey times. As a result, it causes a lot of confusion among all partners, leading to problems such as the inability to accurately detect their food, delivery partners extend the waiting period at restaurants or restaurants not knowing where shipping partners are while food partners get cold. Cold. we introduce time forecasts, we replace the two main factors from assumptions to machine learning-based forecasts. The first is the prediction of food preparation time. Instead of using 25 minutes for all orders from the same restaurant, we use a trained machine learning model to make a forecast for each order, which is 30 minutes in the following example. Delivery system – sends time At the same time, instead of using 5 minutes for all delivery partner travel times, we also use machine learning models to estimate eligible delivery partner travel times, which is why we started sending 10 minutes before food prepared time in examples. Satisfaction from all partners improved significantly. Feeners can deliver fast with clear expectations. Both restaurants and shipping partners become more efficient so they can complete more orders over a period of time. Moreover, our shipping platform also shifts from greed to globally matching algorithms. Greedy matching algorithms only start searching for shipping partners when there are incoming orders. The result is optimal for one order but not for all orders in our system from a global perspective. Therefore, we change to a global matching algorithm so that we can solve the entire order set and delivery partners as a single global optimization problem. what does that mean? Let's do a quick comparison as shown in the following figures. The figures on the left show an algorithm that matches greed. When the first order comes in, our delivery system matches the most eligible delivery partners who will take 1 minute to arrive at the restaurant. Then the second order comes in, the system matches the shipping partner that will take 5 minutes. So the amount of time their journey is 6 minutes. Figures on the right show global matching algorithms where new shipping systems assume both orders and delivery partners at the same time and match them in an optimal way global. As a result, both delivery partners need 2 minutes and their total travel time is only 4 minutes. Delivery system - a comparison between greedy and global algorithms It is evident that the algorithms that match globals are far more efficient. However, it cannot live without precise time forecasts because time is more sensitive and critical to make matching decisions. That's also one of the main reasons that we can only turn to algorithms that match globally after introducing time forecasts. Diving in the forecast of the time Now let's dig details about the forecast of time. As we have seen from the previous section, the food preparation time forecast is very much to business because it is a key factor determining when to send shipping partners. As mentioned earlier, one of the biggest challenges while using machine learning in the O2O business model is the soil truth collection, and the forecast food preparation time is typical Here. Since we are not physical in restaurants and restaurants have no incentive to provide relevant information, it is almost impossible to know when food will be ready. All we can do is use other signals from delivery partners and restaurants to conclude land permission. However, it is not always accurate because of unpredictable conditions such as parking availability, walking to find restaurant entrances, etc. Therefore, we focus on two areas since the beginning. One is how to use available data better than feature engineering, and the other is how to improve model accuracy by concluding label data and harnessing feedback loops for model re-interns. For feature engineering work, it is divided into three sets: historical features such as the average food preparation time for the last week; near real-time features such as average food preparation time for the last 10 minutes; real-time features such as day time, day of the week, order size, etc. The reason we need real-time and near real-time features is that we need additional information to handle some situations that can change quickly. For example, the distribution between orders and delivery partners can be affected by bad weather. One example of our feature engineering work is to leverage delegate learning for chlease type features. In real-time features, we've considered order-specific data such as price, number of goods, etc. However, we do not just want to know how many items in it, we want to know what items are inside because the time of preparing food among different types of cuisine can vary significantly, such as providing a beef stew versus salad. To improve model accuracy taking into account the type of cooking, we use our menu data to generate word cultivation, classify them into different categories, and make them part of real-time features. Learning delegates – Meanwhile, we are constantly exploring more ways to collect new signals to improve the accuracy of inferred label data. Sensor signals from delivery partner's phone are one of them. It is primarily to track the status of shipping partners in some complicated circumstances. For example, if food intake is delayed when their location is close to the restaurant, we need to know whether it is difficulty finding a restaurant or not being able to find the parking lot that causes it. Here we rely on sensor data to predict the next steps based on their current situation. The method sensor signals we use are through field modelling conditional with the target to classify what the current situation is from a set of sequences. By leveraging on these possible models and labeling some travel-seeding data, we are able to predict the activity of the next delivery partner, such as from the parking lot to pick up food. Conditional random field models instead, feedback loops we've introduced for model re-interns also improve our inferred label data significantly. Before digging for more details, I would like to first explain the food preparation time prediction model. We use a tree of gritty results trained with XGBoost and leverage the hyperparameter tuning provided by the Michelangelo platform to improve model accuracy and training performance. The hyperparameter tuning approach in our food preparation time model is bay optimization. Basically, the idea is to allow us to make intelligent choices between all possible combinations of parameters XGBoost may need. Tuning hyperparameter So how does it work? Looking at the plot on the left, the posterior curve shows the 3 combinations of parameters we've tried so far. The larger blue area in the middle shows the part we don't have as much confidence as we haven't tried any combination yet. To find out what combination of what to try next, we created the acquisition function, which tells us what we should try that would provide higher odds to produce better results. The correct plot shows the results after experimenting with the recommended acquisition function of the combination. Now let's go back to the feedback loop we mentioned several times. It is another key component in terms of increasing the accuracy of forecasts due to the lack of soil truth. Since we need to conclude the actual food preparation time, approximate errors always exist between the data that is concluded and real. How to reduce these mistakes is our top priority. We introduce feedback loops into our models to meet budget errors, which help correct the inferred prep time, especially when there are new signals available. For example, we review each complete order to see if we have collected more information to imagine real food preparation time. If so, we use that information to update the inferred values and use it for future model redesignation. Loop feedback Another important feature of the estimated delivery time forecast (ETD), which always affects the time-time of the feeding throughout the order life cycle. For example, every time a meal wonders how long they should wait for their meals, they can check our ETD predictions first. While ETD and food preparation time forecasts share many similar techniques in terms of data processing, feature engineering, etc., there are also many differences between the two. The peakness of ETD forecasts is a variation across different stages as more and more information arises along the way. For example, when the food edryer surfs the restaurant, we only have such as restaurant location, type of cuisine, etc. to make predictions. When the ateer places the order, we will then have more detailed features of the order itself, such as the number of goods, prices, etc. When we've matched shipping partners to pick up the order, we'll have more information from delivery partners, such as their travel time estimates. That's it The ETD prediction model needs to be flexible enough to handle all the variations here. ETD facing the last feature match in time forecasts worth mentioning is the estimated travel time. Uber Eats couldn't grow exponentially in a short period of time without all the support from the rides business. We not only share drivers, but also build heaps of technology on shared platforms. Estimated travel time is one of them. It's very critical for rides because every second thing is for every trip. Riding customers can track their journey from the point of asking for a trip, getting a pick-up, to arrive at the destination. For Uber Eats, the biggest difference is that we have non-car delivery partners, such as riders, pedestrians, etc. In big cities like New York and San Francisco, riders and pedestrians are far more efficient at avoiding overcrowding, parking problems, and more. Making the right travel time forecast for this type of delivery partner is very important for the Eats business. To do so, we work with Uber Maps teams to collect non-car data and train new models separately. The following figures show that the biker has been matched to consume food and that his estimated travel time is 11 minutes. The estimated conclusion of travel time is not a car Now you understand the critical role played by time forecasts in Uber Eats and how we leverage machine learning technology to address some of the toughest problems in the O2O business model. We will definitely continue to invest in this area to move forward and build upper-class machine learning solutions to serve all partners in our three-side market. For more information related to machine learning at Uber, please visit our engineering blog. If you have more specific questions related to time forecasts, feel free to contact me via LinkedIn. About Author Zi Wang is Engineering Manager at Uber, who leads machine learning engineering work for time forecasts including estimated delivery time, food preparation time, and travel time estimates at Uber Eats. In addition, he worked on Uber Eats' shipping system, Uber Rush, and internal payment systems. Before Uber, Zi worked at Microsoft and built real-time collaborative editing features for major Office apps. He is passionate about building highly scalable and prescient backend services as well as leveraging big data and machine learning to solve real-world problems to ensure the efficiency of the system and user experience. Experience.

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