Uber

Uber's Automation for Seamless Pickups Maintains Highs and Lows

Uber: The Evolution from Mass Market to Personalization through AI

Machine learning development has improved opportunities for consumers to enjoy personalized experiences in digital environments, whether through automated watch options on streaming services or product recommendations on e-commerce websites. In the case of Uber, providing personalized experiences is different and challenging as digital and physical experiences collide and external factors like safety, urban compliance, and time management are in play. Uber's approach of developing an ML-based model to aid in pickup difficulties between riders and drivers represents the use of hyper-personalized experiences facilitated by AI. Uber developed a scoring model to determine the confidence of a rider's anchor locations for a seamless pickup, followed by suggestions of pickup locations based on numerous data implications (congestion of traffic and/or crowds, urban hotspots, or previous successful pickup spots.)

In general, marketing has evolved from less targeted, mass communication strategies to customized messages and user experiences thanks to technological advancements, including smart devices, machine learning, and artificial intelligence. In the ridesharing business, the evolution from Taxis to Ubers mirrors this shift. Taxis have a mass communication approach, as any taxi driver looks for any rider they can see, pick up, and charge. While pickup experiences may be more seamless for riders in taxis, the pickup experience is frustrating for drivers who waste time looking for riders. Uber is an organized version of taxi services empowered by technology-based systems that have evolved from traditional cabs. Give or take a few years, and Uber Technologies is meticulously facilitating ridesharing through a sophisticated process involving GPS sensor signals and refined pickup heuristics. Uber offers a more customized experience for riders, who can select from various options like luxury vehicles or carpools, see the price upfront, and manually select a pickup location. Fast forward again, and Uber has utilized AI to handle the pain points for both riders and drivers involved in pickup. When a rider requests a ride, the app will show them a pickup location different from where they're standing. It tells users how many minutes it will take them to walk to the new location, which is usually less than five, and guides them there through a GPS. This feature was implemented to help improve the pickup experience for both riders and drivers, as it directed riders to a pickup spot that would be easier for the driver to find. It takes into account previous locations Uber drivers had successfully picked up riders, and how congested the area is with crowds and traffic, and how specific the location is, like a restaurant, hotel, or a street corner, in which the driver would be easily able to visually pinpoint once arriving. The algorithm also considers the specific user's past behavior on the app and previous pickup locations. A customized pickup location that is proven ideal for the rider based on their rider profile and ride history is supposed to enhance location specificity and make for a seamless pickup experience.

A Customized Experience for Various Segments

Uber's machine learning model incorporates individual customer data, including location patterns, preferences, and behaviors, to create customized predictions and experiences for different customer segments. Uber collected relevant data on riders' locations, such as the GPS coordinates of their anchor location and manual inputs provided by the rider, and rated the location with a confidence score. The score was created based on a hypothesis, determined based on the rider's profile, and the characteristics of the location. (Example: If the rider is requesting a ride from the same restaurant they were dropped off at an hour ago, they should be picked up in the exact spot they were dropped off.) Hypothesized information about pickup locations helps determine if the anchor location makes for a doable pickup spot or not, with the overarching goal of facilitating an easy pickup for both riders and drivers. Customized experiences mean each rider has unique responses from the application. Customization in pickup locations is different yet still useful for each rider segment. **Premium riders** who opt for Uber Select or Uber Black expect longer pickup times and personalized features like temperature, beverages, or music. The machine learning model should rely on the user's anchor location more heavily in this case because the positive experience for the rider is considered more than that of the driver. After all, the rider is generating more revenue for Uber. **High-frequency** riders who take consistent short rides in urban cities expect quicker pickup times, posing a challenge to drivers dealing with densely populated areas. Tall buildings in urban settings also damage the GPS signal and accuracy. ML that decides on pickup locations and adapts them accordingly would be helpful to drivers in this scenario, as the app quickly locates a nearby spot that is less populated and is also feasible for the rider to quickly find. Identifying convenient locations before arrival will speed up the pickup process. **Commuters** whose pickup and drop-off locations are repetitive also request speedy service, and data on their previous rides should be more heavily considered in the algorithm to ensure equally efficient pickups despite different drivers. If a location has been used multiple times by one user, that exact location should be predicted for ride requests from that user and sent to the driver. Ideally, the commuter would expect to be picked up at the same location every time. **Social** riders are often picked up in groups at busy venues at late hours, and since these riders are sometimes inebriated, the pickup experience should be as user-friendly as possible to ensure all participants find the car and get home safely. In these cases, using the anchor location or simply meeting right in front of the venue will be ideal. Navigating to a new pickup location is too complicated for groups and inebriated riders, and time management is not as important for these riders as they're commuting for fun and are less likely to be on a strict schedule compared to commuters. Lastly, **travelers** can be trickly due to densely populated airports, but organization of pickup spots (ex. Terminal 3, section 4) can speed up and increase the ease of pickup. GPS sensors working together with machine learning and UX enable the app to suggest the appropriate pickup location and navigate the traveler to the ideal spot.

Potential Marketing Benefits

This hyper-personalized approach for pickup moderation improves customer satisfaction, retention, and lifetime value, as customers who undergo personalized experiences are more likely to be satisfied and remain loyal. While each segment has different expectations for pickup time length and varies in the nature of their locations, the ML that Uber has implemented has allowed each segment to be uniquely satisfied. Successfully catering to a diverse market allows Uber to grow its customer base, ratings, and profit.

Implementation Challenges

However, implementation challenges are likely to arise. Inaccuracies of GPS and location data, especially in dense urban areas with tall buildings, can make pinpointing exact pickup spot locations difficult. Areas of poor connectivity, including lost GPS signals in tunnels, are also challenges. Outside conditions, including traffic and road closures, can increase pickup time due to no fault of the application. Miscommunication is still an issue, as riders may not be familiar with the designated pickup spots, causing delays or miscommunication. Preferences for specific pickup points (e.g., avoiding busy intersections) may not always align with Uber's optimized locations. Furthermore, processing large volumes of data involving location, traffic, and user preference in real time requires robust machine learning models and high computing power, and ensuring low-latency responses while factoring in live conditions are generally complex. Variations in personalized recommendations across cities may lead to less than ideal pickup locations and cause user frustration. Overcoming these challenges requires continuous AI improvements, adaptive routing, and clear rider-driver coordination.

Dynamic Pricing Revenue Optimization

As mentioned in the Northwestern Kellogg case for Uber, surge pricing is a pain point for riders calculated by AI, especially for social riders who often encounter these surges on evenings and weekends. Surge pricing is certainly an opportunity for revenue optimization, as riders who need transportation have no option but to pay the high prices. On the upside, higher prices encourage more drivers to get on the road, helping balance supply and demand. It also means Uber makes more money per ride when people are willing to pay extra for convenience. Plus, personalized pricing can help the company fine-tune fares based on rider behavior, making sure they're charging what people are willing to pay. When done right, it keeps the system efficient, drivers happy with better earnings, and Uber's bottom line growing.

“Price Surge” Ethical Concerns

Riders in emergency situations are disproportionately affected and exploited. Low-income riders are also affected, and dynamic pricing algorithms may lead to perceived price discrimination where some users pay significantly more based on behavioral data rather than pure supply-demand economics. Hyper-personalized pricing creates an imbalance between fairness for riders and adequate compensation for drivers. The lack of transparency in how prices are set can make it seem like some riders are being charged more just because an algorithm thinks they’ll pay it. At the same time, Uber has to balance keeping fares reasonable for riders while making sure drivers are fairly paid. To keep things ethical, there needs to be more clarity around pricing, limits on extreme price spikes, and some indication of emergency so price surges will not take advantage of people when they need a ride the most.

NOTES

- Uber Technologies has utilized machine learning to help determine ideal pickup locations. When a rider requests a ride, the app will now show them a pickup location different from where they are standing. It tells users how many minutes it will take them to walk to the new location, usually less than five, and navigate them through GPS. This feature was implemented to help improve the pickup experience for both riders and drivers.
- The “Anchor location” is an Uber rider's original location, determined by GPS tracking. The anchor point is given a “confidence score.” A high confidence score indicates the driver is likely to find the rider with ease at the anchor location, and a low confidence score indicates the opposite.
- The confidence score was created based on a hypothesis, created based on the rider’s profile, the characteristics of the location, etc. An example hypothesis includes: If a rider was recently dropped off at a location, like a restaurant or event venue, it was likely that he or she was still there if they are requesting a ride an hour later. Hypothesized information about pickup locations helps determine if the anchor location makes for a doable pick up spot or not.

- **Rider segments:** premium, high-frequency riders, commuters, social, travelers
- **Performance metrics** are based on a variety of factors. Quantitative data includes how many steps the rider took from where they were waiting to where the car was waiting, how many minutes the driver waited, cancellation rates, customer ratings, etc. Messages and/or phone calls initiated by riders or drivers to find each other are relevant data for America, as Americans only contact one when they have trouble, while in India, communication is standard for all rides.

Works Cited

Sawhney, Mohanbir, et al. "Uber: Applying machine learning to improve the customer pickup experience." *Kellogg School of Management Cases*, 15 Nov. 2019, pp. 1–21, https://doi.org/10.1108/case.kellogg.2021.000090.