Neural Contextual Bandit Pricing

Based on insights derived from data collected by data analysts through Tableau dashboards and user/driver feedback gathered from online forums and weekly interactions with random drivers, a critical pricing challenge has been identified. Approximately 30 percent of ride previews fail to convert into ride proposals due to perceived high prices, while 50 percent of ride proposals are left unaccepted by drivers, leading to a lack of active rides, often attributed to unreasonably low prices.To address this issue and optimize the pricing strategy, the company requires a dynamic and adaptive pricing system capable of considering numerous factors such as estimated time of arrival (ETA), time of day, the supply-demand ratio, and the duration it takes for a driver to accept a ride proposal or for passengers to accept a ride preview. This complex challenge is framed within the context of a multi-armed bandit problem, and we address it using a neural contextual bandit algorithm.

- Utilize a deep neural network architecture to model the complex reward function, addressing the challenge of handling a multitude of factors and variations in each state of the pricing problem.
- Implement the experience replay method to break correlations in sequential samples, facilitating stable and efficient updates of the neural network parameters.

Following two months of fine-tuning the parameters of the Deep Neural Network (DNN) within the Neural Contextual Bandit pricing system, continuous monitoring of business metrics reveals notable improvements. The initial challenge, where 30 percent of ride previews failed to convert into ride proposals due to perceived high prices, has seen a significant reduction to 20 percent. Simultaneously, the issue of 50 percent of ride proposals being left unaccepted by drivers, resulting in a lack of active rides, has decreased to 35 percent.