Multi-objective Online Optimization Problems: Matching Drivers to Passengers in Ride Sharing Markets

We study a class of multi-period multi-objective online optimization problems, where a decision maker takes actions over time in an online fashion without being informed of future scenarios. To balance the trade-offs between different objectives, we develop an efficient online policy to derive the “compromise” solution, which minimizes the $l_p$-distance from the attained KPIs to the utopia target for any $0 \leq p \leq \infty$. More precisely, we aim to achieve a solution that has the smallest deviation, based on some pre-determined distance function, to an “utopia point”, i.e., an ideal solution maximizing the performance of all objectives, but is otherwise non-attainable at the same time. Furthermore, we show that the online policy induces a randomized solution to a related class of stochastic single-period multi-objective problems. This online policy can also be used to check the feasibility of the given multi-objective targets. Whenever the targets are located within the efficient frontier, the attained results using this policy can achieve this target. However, if the target cannot be achieved, this implies the infeasibility of the target.

Multi-objective optimization has had broad applications in both academic and industrial fields, including science, engineering, and economics, where optimal decisions need to be taken in the presence of trade-offs between two or more conflicting objectives. We apply the online policy in ride sharing market settings, and provide an online matching policy that simultaneously incorporates driver service scores, pick-up distances and passenger revenues. We note that in the ride sharing market, the platform operator would want to dispatch more jobs to drivers with higher service rating. This helps to retain the better drivers in the system, and provide better service experience to the customers. However, this could not come without sacrificing the average pick-up distance between dispatched drivers and passengers. Moreover,
the platform needs to manage the impact on the bottom line - longer waits lead to lower answer count (passengers drop the bookings) and lower revenue. To balance these different Key Performance Indexes (KPIs), three key considerations need to be taken into account to design the matching policies in these markets: (1) Passengers with higher revenues should be served with higher priority; (2) Passengers' waiting time for pick-up should be as small as possible; (3) Drivers with higher scores should be dispatched with higher priority.

Note that the traditional approach to multi-objective optimization problem entails a delicate selection of weighting function to aggregate the multiple objectives into a single one, and the central issue there is the choice of the weighting function to be used for aggregation. Our approach exploits the multiple period setting, and the existence of natural performance targets (i.e., the utopia point), to develop an adaptive weighting function that learns from historical performance to drive the algorithm towards the compromise solution. Our detailed numerical studies on the driver dispatching problem show that this approach is able to “learn” from data the appropriate weighting function that can be used in each period to guide the system towards a good matching solution.

We extracted real world data from Didi Chuxing, the largest on-demand ride sharing platform in China. Our dataset contains the ride sharing records of three cities, abbreviated as City A, B, and C. The dataset of City A was used for the numerical validation. We used data from City B and City C for more elaborate industrial implementation, where the matching scenario per period is now endogenous and depends on the matching algorithm used. Compared to legacy policies currently in use, such as the weighted average policy or the “closest distance” policy, we observe that all parties in the ride-sharing eco-system, from drivers, passengers, to the platform, are better off under our proposed online matching policy: (1) drivers with higher service scores are dispatched with more orders; (2) passengers are more likely to be matched to drivers with higher service scores, and passengers with higher revenues (longer travel
distances) are served with higher answer rates; (3) the platform obtains a higher revenue and better long-term brand reputation. For instance, we observe that more jobs are assigned to drivers with higher service quality. Figure 1 demonstrates that expected total revenue earned by drivers with higher service scores (e.g., higher than 101) increases under the CM policy. We also find that the revenue increment for these drivers is indeed due to more orders being dispatched to them. This outcome would motivate drivers to increase their service score by providing better ride sharing service to passengers. In addition, we observe a decreasing trend in total revenue for these drivers with extreme high service scores. One possible explanation is that a large proportion of DIDI drivers are part-time and their revenue also depends on their total business hours (i.e., active time as a driver on the platform). The dataset reveals this pattern: these drivers with service scores in the interval [98, 108] are more active than the ones with scores in the interval [109,116]. Even so, our CM policy dispatches more orders to these drivers with higher service scores consistently.

As a side effect, the total revenue obtained by the platform during the whole day under the our policy also increases by 0.26% in City B and 0.56% in City C, respectively.