CS 269I Proposal: Time-Sensitive Market Matching

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1 Problem formation and incentive-related issues

We examine the matching problem in the ride sharing market, where buyers (e.g., Lyft users) want to be matched with sellers (e.g, drivers or autonomous vehicles), and the goods being sold are rides from place to place. This matching problem is similar to those we studied in class; we wish to find a maximum weight matching. However, this market presents a challenge. Participants arrive at different times then depart after some time period, and participants can only be matched while they are in the marketplace. The platform's matching algorithm, therefore, must perform matches online without full knowledge of future states of the marketplace.

We assume this platform has access to the pairwise utilities of each buyer-seller pair. The valuations and prices to compute these utilities might be shared with the platform, or the platform might compute them as expected profits from each ride. This might take into account the probability of the buyer accepting the ride and the travel time from seller to buyer pickup among other factors. The platform is incentivized to maximize utility in the latter case, as a utility maximizing matching will result in the largest revenue.

We approach this problem by building on material presented in class and in [Ash18]. We will first examine incentive issues in this market, considering revenue maximization by the platform and incentives of the participates drawing from material in class. We will then define a full model and simulate this market to evaluate algorithms of Ashlagi *et al.* [Ash18], and we will use these evaluations as a baseline. We then plan to extend the work in [Ash18] to account for additional factors in the marketplace.

2 Data

For this project we will use simulated data. For example, a two dimensional matrix where buyers and sellers appear and disappear at some given or random interval. At any given moment, we know which buyers and sellers are in the marketplace with a process as simple as a mask over the matrix. We also must know the value of any buyer-seller pair for the matching algorithm to work. In the given example, the inverse distance between a buy and seller in the two-dimensional grid world would suffice for a simple value function.

Pending time constraints, we will search for datasets that we can access with the desired qualities: (1) buyers and sellers appearing and disappearing from the marketplace and (2) an easy to represent value function for all buyer-seller pairs. One potential example would be the kidney transplant market.

3 Model

We will implement the algorithms proposed in [Ash18] and introduce directed modifications in order to observe changes in output, if any (see Section 4). To understand the algorithms, it is imperative to first establish the model. To this end, we consider a weighted graph G on n nodes (indexed by $i = 1, 2, , n$), where the nodes arrive sequentially over n periods. We denote the arrival time of node i by $\sigma(i)$ and the weight on edge (i, j) as w_{ij} (where the edge, and therefore the weight, are only observed once the later of the two nodes arrives). Additionally, for deadline d, we assume that edge (i, j) exists if and only if $|\sigma(i) - \sigma(j)| \leq d$. Finally, for simplicity, we will define the weight w_{ij} such that it is inversely proportional to the Euclidean distance between i and j.

We will assume the weights are drawn from some distribution, so we set $\sigma(i) = i$. The algorithm, termed *Postponed Greedy*, proceeds as follows: an arriving node k is added to a virtual graph as both a buyer (b_k) and a seller (s_k), s_k starts out without being connected to any of the available buyers while b_k is connected to the other available sellers, the *Greedy* algorithm (Feldman et. al. [Fel09]) is run on the virtual graph. In [Ash18], an equivalent procedure is proposed, called Dynamic Deferred Acceptance, in which a tentative maximum-weight matching is maintained at all times during the algorithm.

4 Model limitations and extensions

After implementing the model and algorithms in [Ash18] as a baseline, we will extend the model to include various practical limitations and phenomena currently unaccounted. While we anticipate that the exact nature and number of these extensions may change during the implementation process, we consider here a number of possible extensions.

Incorporate wait-time into value In the current model given by [Ash18], match values are static, depending only upon the individuals being matched. In a ride sharing system, however, intuition suggests that riders who have been waiting longer will find greater value in being matched. As a proof-of-concept, we will first assume that this wait-dependency is linear over time with a consistent slope across riders; however, if time permits, we will also consider other, more personalized dependency functions.

Include look-ahead In an attempt to capture a market where rides may be either reserved in advance or booked in the moment, we will consider the case where some riders' arrival time is known in advance (e.g., with "look-ahead," as discussed in [Ash18]) while others appear at the moment of arrival.

Enable knowledge of distribution of departures Ashlagi *et al.* introduce the "stochastic departures" in [Ash18], where each rider leaves after an arbitrary amount of time rather than a consistent deadline d. However, even in this case, it is assumed that the matching algorithm knows with certainty when the deadline becomes critical. We purpose introducing the possibility of wrong assumptions into our model. Instead of telling the algorithm when a deadline becomes critical, we will consider the case where the algorithm knows the distribution of departure deadlines *a priori* but does not know the specific departure deadline for any given rider, even when that deadline becomes critical.

5 Evaluation

We will perform extensive empirical evaluations for this project. First, we will contextualize our simulations of the algorithms in [Ash18] with the theoretical results in the paper. We will then compare the values of the output matchings for our approach that incorporates the additional information to the approaches in [Ash18]. We will also report other, more insightful metrics. For example, what portion of buyers/sellers are never matched by the algorithms? What are the variances of the matchings? Are some algorithms more prone to outliers, or more willing to sacrifice lower-quality matchings? These are example questions we hope to answer through the empirical evaluation we will perform.

References

[Ash18] Burq M. Dutta C. Jaillet P. Saberi A. Sholley C. Ashlagi, I. Maximum Weight Online Matching with Deadlines. *ArXiv e-prints*, August 2018.

[Fel09] Korula N. Mirrokni V. Muthukrishnan S. Pal M. Feldman, J. Online ad assignment with free disposal. *International Workshop on Internet and Network Economics*, pages 374–385, 2009.