RE-ORG: An Online Repositioning Guidance Agent

Demonstration

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ABSTRACT

Continuous matching of supply and demand through online/real-time decision making is a problem of critical importance in many urban environments. [1–4, 7, 9, 10]. Examples include bike/scooter sharing systems, car sharing, food/ grocery delivery, smart vending machines and other similar aggregation systems. In these systems, apart from supply (e.g., bikes/scooters, cars, restaurants/supermarkets) and demand (e.g., customers), there may also be matching resources that help match supply and demand (e.g., trucks, car drivers, delivery boys). The success of these systems depends on the ability to have supply available at the “right" locations at the “right" time.

The matching decisions taken by the company operators are typically performed based on the current status of supply, demand and location of matching resources. In this paper, we present RE-ORG (**R**epositioning ag**E**nt for **O**nline spatio-tempo**R**al matchin**G** problems) to provide guidance for matching resources to have supply at the right locations at the right time to serve demand. Apart from providing the guidance on matching decisions, RE-ORG also provides a real time status of the supply, demand and matching resources.

KEYWORDS

Sequential Matching, Repositioning guidance, optimization

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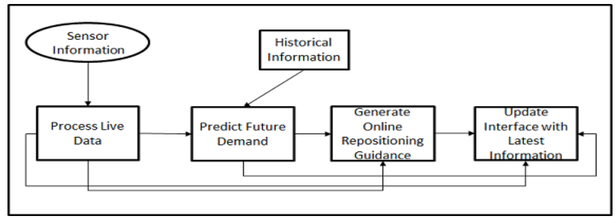
1 RE-ORG: AN ONLINE REPOSITIONING GUIDANCE AGENT

We present the details of RE-ORG in this section. As shown in figure 1, there are four major components of RE-ORG [1].

1.1 Processing of Live Data

All resources and carrier vehicles are equippped with sensors. Every few seconds, the inputs from all the active resources and carrier vehicles are processed and stored in a database. In addition to the location of the carrier vehicle and resources, we also store the number of resources available in vehicles and stations. As the city contains thousands of locations/stations, to make the system scalable, we divide the city into multiple regions and the position of each resource and vehicle is mapped to a region.



(a)

Figure 1: RE-ORG - An Online Repositioning Guidance Agent

1.2 Prediction of future demand

The online repositioning algorithm needs the future demand samples for providing better guidance. Therefore, the second component of the system helps in predicting the demand of resources in each region based on the current status and the historical information stored in the database. As the historical data only contains successful transactions and does not capture the unobserved lost demand, we employ a micro-simulation model with 1 minute of timestep to identify the duration when a station got empty and introduce artificial demand at the empty station based on the observed demand at that station in previous timestep [5]. This component can be updated to a sophisticated prediction model based on poisson process and choice modelling [6].

1.3 Online Repositioning Guidance

The Online Repositioning Guidance algorithm is based on the multistage stochastic optimization model proposed in [8]. We assign vehicles to different regions and solve each region separately. We solve the optimization model presented in Table 1 for each region. The objective of the optimization model is to minimize the expected lost demand over $|F|$ demand samples [2] for next Q timesteps. We use $L_s^{t,k}$ to denote the lost demand at station s at timestep t in sample k. The lost demand is computed as a difference between available demand and the number of hired/consumed resources. The model uses the current position of vehicles [3], vehicle capacities (C_v^*) and the availability of resources at different stations.

The guidance provided to vehicles is represented by two sets of variables in the optimization model. The y variables are used to denote the number of resources to be picked up/dropped off from station by carrier vehicles. The z and m variables provide the routing decisions and are used to determine the next station to be

[1]The video demonstrating the repositioning agent can be found at https://www.dropbox.com/s/ugy4ne8vkcm3k5s/Re-Org.mp4?dl=0

[2]The predicted demand in previous step is used for generating multiple demand samples.

[3]$\sigma_v^0(s)$ is set to 1 if vehicle v is present at station s at current timestep

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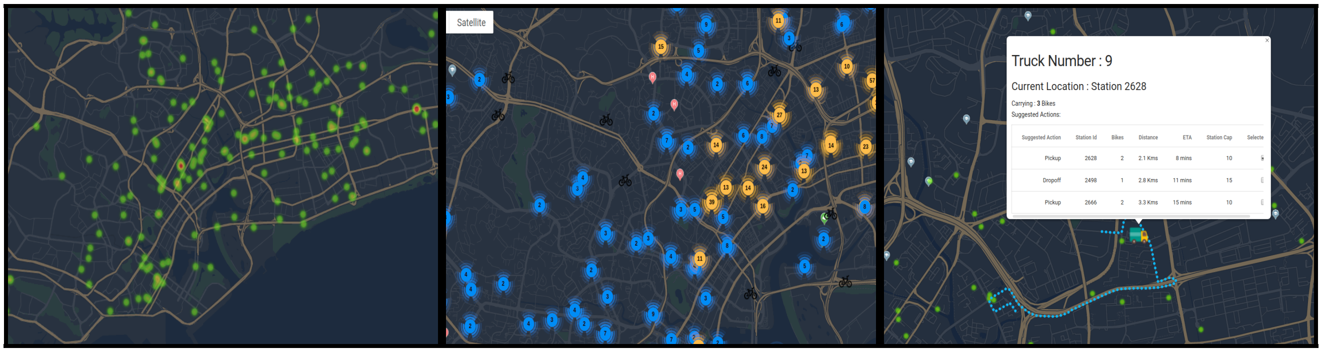

(a) (b) (c)

Figure 2: (a) Demand Layer - current information (b) Supply Layer - availability of resources (c) Matching Layer - suggestions

visited by vehicle. The constraints (2)-(3) ensure that a vehicle v picks up/drops resources at a station only if it visits that station. Other constraints [4] in the optimization model ensure that (1) Flow of resources in and out of stations are preserved, (2) Flow of resources between any two stations is as per the demand samples, (3) Station and Vehicle capacity constraints are satisified and (4) Movement of vehicle across timesteps is valid.

$$\min \quad \frac{1}{|F|}\sum_{t=0}^{Q-1}\sum_{k}\sum_{s} L_s^{t,k} \tag{1}$$

$$y_{s,v}^{+,0} + y_{s,v}^{-,0} \leq C_v^* * \sigma_v^0(s) \;:::\; \forall s, v \tag{2}$$

$$y_{s,v}^{+,t,k} + y_{s,v}^{-,t,k} \leq C_v^* * z_{s,v}^{t,k} \;:::\; \forall s, v, t > 0, k \tag{3}$$

$$Other\ Constraints$$

$$z_{s,v}^{t,k}, m_{s,v}^{0,t}, m_{s,v}^{t,t',k} \in \{0, 1\}$$

Table 1: Optimization Formulation

This optimization model is run continuously in a rolling horizon manner in order to provide real time repositioning guidance. We also run the optimization model with different set of samples to provide multiple options to company operators.

1.4 Interface

The system interface (Figure 2) is built using Django and Mysql is used for storing the data. Django is a python web framework which is highly scalable and hence is very useful in our case. The interface shows the real time bird's eye view about all the demand, supply and the matching information in the form of marker clusters. The marker clusters can be zoomed in to a finer level for more specific information about a particular station/location.

The interface consists of three main layers, Demand, Supply and Matching Layers. The operator has an option to toggle any of these layers on the map according to convineance. The Demand Layer shows the real time information about the predicted demand on the map. The Supply Layer shows the availability of resources across different stations on map. Marker clusters are used to display the large number of markers on the map. On zooming in, the resources/demand at each location is shown. The Matching Layer consists of different vehicles for repositioning. For each vehicle, this layer shows live status information like the distance travelled, resources on board, fuel left. This layer also shows the multiple routes suggested by our repositioning algorithm for each vehicle. Each option for the vehicle involves the route to be taken and number of resources which should be picked up or dropped off at each station/location along the route. The operator has an option to choose one of these decisions. If the operator does not select an option within few minutes, the default option is chosen by the system and is communicated to the drivers.

(a)

Figure 3: Results

All the layers are updated at regular intervals using the data stream from the sensors on board of the vehicles/resources. The frequency of the update can be set by the operator. Apart from these layers, the interface provides a tab featuring Data Analysis by providing different statistics such as average fuel consumed, expected reduction in the lost demand etc.

2 RESULTS

We evaluate the efficiency of our repositioning system on a real world bikesharing dataset. Figure 3 shows the percentage reduction in lost demand as compared to a static repositioning approach used by operators. The different scenarios correspond to different intial distrbitution of bikes. The least percentage reduction of 17% is obtained when bikes are uniformly distributed across different locations initially and the highest reduction is obtained when the bikes are initially made available only at 10% of all available stations.

3 ACKNOWLEDGEMENTS

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[4]Please refer to [8] for detailed model.

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