Improving Customer Satisfaction in Bike Sharing Systems through Dynamic Repositioning

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Motivation: Bike Sharing Systems

- **Bike Sharing Systems (BSS)**
  - 1700 active systems all over the world
  - Attractive alternative to private vehicles
  - Reduce traffic congestion, greenhouse gas emission, and air pollution

- **Problem**: Starvation or congestion of bikes at stations
  - Increase usage of private vehicle and carbon emission

- **Goal**: Repositioning of bikes during the day to address availability issues

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**Figure 2**: Number of empty and full instances of stations in Capital Bikeshare Company

Due to a trivial reduction from the existing Static Bicycle Repositioning Problem (SBRP), which is NP-Hard (Schuijbroek et al., 2013), DRRP is at least NP-Hard. Therefore, we focus on developing principled approximation methods. Our key contributions are as follows:

1. A mixed integer linear program (MILP) formulation to maximise profit for the bike sharing company that considers the trade-off between:
   - Maximising served demand
   - Minimising cost incurred by vehicles
2. A dual decomposition mechanism to decompose the MILP into two components—one which computes repositioning solutions for bikes and one that computes routing solutions for vehicles.
Background: Repositioning in Bike Sharing

- Static repositioning (at the end of day)
  - Raviv and Kolka (2013), Raidl et al. (2013)

- Dynamic repositioning (myopic & offline)
  - Schuijbroek et al. (2013), Shu et al. (2013)

- Repositioning using incentives
  - Singla et al. (2015), Ghosh et al. (2017)

- Robust repositioning under demand uncertainty
  - Ghosh et al. (2016)

- Our contribution:
  - Using satisficing approach to tackle the demand uncertainty
Satisficing Approach

- Tractable satisficing approach [Jaillet et. al. 2016]
  - Constraints are defined over uncertain variables.
  - Maximize the probability of satisficing feasibility constraints.

\[
\max \rho(\alpha) \\
\text{s.t. } A(z)x \geq b(z) \forall z \in \mathcal{U}(\alpha)
\]

- Taking satisficing approach to bike-sharing system
  - Support set for station s:
    \[W_s = \{\zeta^1_s, ..., \zeta^n_s\} = \{1, 2, 3\}\]
  - Realization probability:
    \[\chi^2_s = P(\bar{z}_s \leq 2) = 3/4\]
  - Objective:
    \[
    \max \sum_s \log(P(\bar{z}_s \in W_s))
    \]
Optimization Model

- **Input tuples:** \( S, \mathcal{V}, C^#, C^*, d^#, 0, \{\sigma_v^0\}, P, F \)
  - Stations
  - Vehicles
  - Station Capacities
  - Vehicle Capacities
  - #bikes in stations
  - #vehicles in stations
  - Routing Costs
  - demand Scenarios

- **Outputs:** Repositioning & routing strategy

- **Decision Variables:**
  \[ \alpha^l_s \in \{0, 1\} : 1 \text{ if } \zeta^l_s \text{ is selected as demand bound} \]
  \[ y^+_s, y^-_s : \text{Total number of bikes picked up and dropped off from station } s \]
  \[ z^r_{s,v} \in \{0, 1\} : \text{Set to 1 if vehicle } v \text{ is stationed at } s \text{ at episode } r \]

- **Objective:**
  \[ \max_{y^+, y^-} \sum_s \sum_l \alpha^l_s \log(\lambda^l_s) \]
  - Realization probability of \( l\)-th demand entry in support set
  - Maximize log-likelihood of meeting realized (uncertain) demand
Problem Constraints

- **Feasibility constraints**
  \[
  \sum_{l} \zeta_{s}^l \alpha_{s}^l \leq d_{s}^{#} + y_{s}^{-} - y_{s}^{+} + \rho_{s} \quad \forall s
  \]

  \[
  \sum_{l} \zeta_{s}^l = 1 \quad ; \quad \sum_{s} \rho_{s} \leq \rho
  \]

- **Routing constraints:**
  - A vehicle can only be at one station at any episode.
Problem Constraints

- Feasibility constraints
  \[ \sum_{i} \zeta_s^i \alpha_s^i \leq d_s^# + y_s^- - y_s^+ + \rho_s \quad \forall s \]
  \[ \sum_{i} \zeta_s^i = 1 \quad ; \quad \sum_{s} \rho_s \leq \rho \]

- Routing constraints:
  - A vehicle can only be at one station at any episode.
  - Time spend in routing & repositioning is bounded by duration of decision period.

- Repositioning constraints
  - Flow preservation of bikes at vehicles.
  - Reposition at a station is possible only if a vehicle is present there.

\[ y_{s,v}^+ + y_{s,v}^- \leq \gamma_{s,v}^r \quad \forall s, v, r \]
Experimental Setup

- **Dataset:**
  - Hubway (95 stations, 3 carrier vehicles)
  - Trip history data for 3 months
  - Planning period: 6AM-12PM (each decision epoch is 30 minutes)
  - Training data: 20 days of demand scenarios
  - Testing data: 40 days of demand scenarios

- **Evaluation Metrics:** Average and worst-case lost demand over all testing demand scenarios.

- **Approaches:**
  - Static (Redeployment at the end of day)
  - Offline approach [Shu et. al., (OR Journal, 2013)]
  - Online approach [Schuijbroek et. al., (EJOR Journal, 2017)]
  - Robust approach [Ghosh et. al., (IJCAI, 2016)]
  - DrROBUST (our approach using satisficing)
Experimental Results

- A vehicle is allowed to visit a maximum of 3 stations (R=3):
  - Our Satisficing approach reduces the average lost demand by at least 15% over all the benchmarks.
  - The worst-case lost demand is reduced by at least 5%.
Experimental Results

- A vehicle is allowed to visit a maximum of 4 stations (R=4):
  - Our Satisficing approach reduces the average lost demand by at least 19% over all the benchmarks.
  - The worst-case lost demand is reduced by at least 9%.
Runtime performance

- DrROBUST is more computationally attractive than Robust approach for 3 episodes per decision epoch.
- For 4 episodes per decision epoch, DrROBUST has highest runtime complexity, but runtime is always bounded by 15 minutes.
Concluding Remarks

- Robust repositioning in Bike Sharing Systems
  - A practically important and challenging problem.
  - A tractable satisficing approach is adopted to maximize the log-likelihood of meeting uncertain future demand.
  - Solutions are validated on a simulator built on a real-world data set.
  - Lost demand (average) is reduced by at least 15%.
  - Solution is robust to uncertainty in future demand.

- Future Direction:
  - How to adapt the solution approach to tackle the problem in the context of dockless bike sharing systems?
  - How to consider future demand for multiple time-steps to further reduce the lost demand?
Supplementary Slides
Simulation Model

- Compute flows of customers between stations given the distribution of bikes

\[
x_{s,s'}^t = \begin{cases} 
  f_{s,s'}^t & \text{if } \sum_{s'} f_{s,s'}^t \leq d_{s}^{t} \\
  \frac{f_{s,s'}^t}{\sum_{\tilde{s}} f_{s,\tilde{s}}^t} \cdot d_{s}^{t} & \text{otherwise}
\end{cases}
\]

Actual flow depends on demand and supply of bikes

- Compute distribution of bikes for next decision epoch

\[
d_{s}^{t+1} = d_{s}^{t} + \left[ \sum_{\tilde{s}} x_{\tilde{s},s}^t - \sum_{s'} x_{s,s'}^t \right] + \left[ Y_{s}^{-,t+1} - Y_{s}^{+,t+1} \right]
\]

Net drop-off bikes by carrier vehicles

Net inflow of bikes by customers

Net inflow of bikes by customers

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Routing Distance Comparison

- Robust approach reduces the average and worst-case lost demand by at least 18% and 17% over all the benchmarks.
- Satisficing approach further reduces the average and worst-case lost demand by 26% and 14% over the Robust approach.