Dynamic Redeployment to Counter Congestion/Starvation in Vehicle Sharing Systems

**Supriyo Ghosh, Pradeep Varakantham**
School of Information Systems, Singapore Management University

Yossiri Adulyasak, Patrick Jaillet
Singapore MIT Alliance for Research and Technology (SMART), MIT
Motivation: Bike Sharing Systems

- Examples
  - Bike Sharing (Capital Bikeshare, Hubway, etc.): 747 active systems
Motivation: Bike Sharing Systems

- Examples
  - Bike Sharing (Capital Bikeshare, Hubway, etc.): 747 active systems
- Alternative transportation to reduce carbon emissions and traffic congestion
Motivation: Bike Sharing Systems

- Problem: Lost demand because of insufficient vehicles at right places/times
- Increased use of private transportation and hence carbon emissions
- Reduced revenue
Related Work

- Static Redeployment (once at the end of day)
  - Raviv and Kolka (2013), Raviv et al. (2013), Raidl et al. (2013)
  - Issue - Stations are imbalanced during the day.
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- Dynamic Redeployment (matching of producer and consumer station)
  - Shu et al. (2013, 2010), O’Mahony and Shmoys (2015)
  - Issue - Does not consider the routing cost which is a major cost driver.
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- **Myopic/Online Redeployment**
  - Schuijbroek et al. (2013), Pfommer et al. (2014), Singla et al. (2015)
  - Issue - Perform poorly in reality as it does not consider the future demands.
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- **Our Approach:**
  - MILP to jointly consider dynamic routing and redeployment problem *[DRRP]*
  - Lagrangian dual decomposition to improve the scalability.
  - Abstraction mechanism by grouping the nearby base stations to reduce the decision problems.
Challenge

- Input: A DRRP is compactly defined using following tuple

\[ \langle S, V, C^\#, C^*, d^\#, 0, d^*, 0, \{\sigma_v^0\}, F, R, P \rangle \]
Challenge

- Input: A **DRRP** is compactly defined using following tuple

\[ \langle S, V, C^#, C^*, d^#_0, d^*_0, \{\sigma^0_v\}, F, R, P \rangle \]

- Outputs:
  - Number of vehicles to be redeployed, \( y \)
  - Routes for carriers, \( z \) to make redeployments
Challenge

- Input: A DRRP is compactly defined using following tuple
  \[
  \left( S, V, \#C, C^*, d^#, 0, d^*, 0, \{\sigma^0_v\}, F, R, P \right)
  \]

- Outputs:
  - Number of vehicles to be redeployed, \( y \)
  - Routes for carriers, \( z \) to make redeployments

- Objective: Maximize revenue (increasing satisfied demand + reducing carrier fuel costs)
Approach: Linear Optimization

\[
\min_{y^+, y^-, z} - \sum_{t, k, s, s'} R_{s, s'}^t k \cdot x_{s, s'}^t k + \sum_{t, v, s, s'} P_{s, s'} \cdot z_{s, s', v}^t
\]

Maximize revenue
Approach: Linear Optimization

Maximize revenue

Flow preservation of bikes at stations
Approach: Linear Optimization

\[
\min_{y^+,y^-,z} \sum_{t,k,s,s'} R^{t,k}_{s,s'} \cdot x^{t,k}_{s,s'} + \sum_{t,v,s,s'} P_{s,s'} \cdot z^t_{s,s',v} \\
\]

Maximize revenue

Flow preservation of bikes at stations

Actual flow \(\propto\) Observed Flow

\[
d^\#_{s} + \sum_{k,\bar{s}} x^{t,k}_{\bar{s},s} - \sum_{k,s'} x^{t,k}_{s,s'} + \sum_{v} (y^{-,t}_{s,v} - y^{+,t}_{s,v}) = d^\#_{s} + 1, \ \forall t, s
\]

\[
x^{t,k}_{s,s'} \leq d^\#_{s} \cdot \frac{F^{t,k}_{s,s'}}{\sum_{k,\bar{s}} F^{t,k}_{s,\bar{s}}}, \ \forall t, k, s, s'
\]
The right trade-off between minimizing lost demand (maximizing revenue) and reducing cost due to carriers.

We employ a data driven approach to solve DRRP. That is set partitioning problem, a known NP-Hard problem.

\[
\min_{y^+, y^-, z} \sum_{t, k, s, s'} R_{s, s'}^t \cdot x_{s, s'}^t, k + \sum_{t, v, s, s'} P_{s, s'} \cdot z_{s, s', v}^t
\]

Maximize revenue

Flow preservation of bikes at stations

\[
d_s^#, t + \sum_{k, s} x_{s, s}^t, k - \sum_{k, s'} x_{s, s'}^t, k + \sum_v (y_{s, v}^-, t - y_{s, v}^+, t) = d_s^#, t+1, \forall t, s
\]

Actual flow \(\propto\) Observed Flow

Flow preservation of vehicles in carriers

\[
x_{s, s'}^t, k \leq d_s^#, t \cdot \frac{F_{s, s'}^t, k}{\sum_{k, s} F_{s, s'}^t, k}, \forall t, k, s, s'
\]

\[
d_v^*, t + \sum_{s \in S} [(y_{s, v}^+, t - y_{s, v}^-, t)] = d_v^*, t+1, \forall t, v
\]
Approach: Linear Optimization

\[
\text{Minimize} \quad y^+, y^-, z \quad \text{subject to} \quad \sum_{t,k,s,s'} R_{s,s'}^{t,k} \cdot x_{s,s'}^{t,k} + \sum_{t,v,s,s'} P_{s,s'} \cdot z_{s,s',v}^{t} \leq 0
\]

\[
d_{s}^{\#}: t \left( \sum_{k,s} x_{s,s}^{t,k} - \sum_{k,s'} x_{s,s'}^{t,k} + \sum_{v} \left( y_{s,v}^{t} - y_{s,v}^{+,t} \right) \right) = d_{s}^{\#} + 1, \quad \forall t, s
\]

\[
x_{s,s'}^{t,k} \leq d_{s}^{\#} \cdot \frac{F_{s,s'}^{t,k}}{\sum_{k,s} F_{s,s}^{t,k}}, \quad \forall t, k, s, s'
\]

\[
d_{v}^{*,t} + \sum_{s \in S} \left[ \left( y_{s,v}^{t} - y_{s,v}^{+,t} \right) \right] = d_{v}^{*,t+1}, \quad \forall t, v
\]

\[
\sum_{k \in S} z_{s,k,v}^{t} - \sum_{k \in S} z_{k,s,v}^{t-1} = \sigma_{v}^{t}(s), \quad \forall t, s, v
\]

\[
\sum_{j \in S, v \in V} z_{s,j,v}^{t} \leq 1, \quad \forall t, s
\]

Maximize revenue

Flow preservation of bikes at stations

Actual flow $\propto$ Observed Flow

Flow preservation of vehicles in carriers

Enforcing right movement of carriers between stations

<table>
<thead>
<tr>
<th>Category</th>
<th>Decision Variable</th>
<th>Description</th>
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<tbody>
<tr>
<td></td>
<td>$y^+, y^-, z$</td>
<td>Flow of bikes in stations</td>
</tr>
<tr>
<td></td>
<td>$x_{s,s'}^{t,k}$</td>
<td>Flow of bikes in carriers</td>
</tr>
<tr>
<td></td>
<td>$P_{s,s'}$</td>
<td>Probability of demand</td>
</tr>
<tr>
<td></td>
<td>$d_{s}^{#}: t$</td>
<td>Number of bikes at stations</td>
</tr>
<tr>
<td></td>
<td>$F_{s,s'}^{t,k}$</td>
<td>Total number of bikes in carriers</td>
</tr>
<tr>
<td></td>
<td>$\sigma_{v}^{t}(s)$</td>
<td>Number of bikes served in vehicles</td>
</tr>
<tr>
<td></td>
<td>$\sum_{j \in S, v \in V} z_{s,j,v}^{t}$</td>
<td>Number of carriers between stations</td>
</tr>
</tbody>
</table>
### Approach: Linear Optimization

\[
\begin{align*}
\min & \quad y^+, y^-, z \\
& \quad \sum_{t,k,s,s'} R_{s,s'}^t, R_{s,s}^t \cdot x_{s,s'}^t + \sum_{t,v,s,s'} P_{s,s'}^t \cdot z_{s,s',v}^t
\end{align*}
\]

\[
d_s^{\#}, t + \sum_{k,\tilde{s}} x_{\tilde{s},s}^{t-k,k} - \sum_{k,\tilde{s}} x_{\tilde{s},s}^{t,k} + \sum_v (y_{s,v}^{-t} - y_{s,v}^{+t}) = d_s^{\#}, t+1, \forall t, s
\]

\[
x_{s,s'}^{t,k} \leq d_s^{\#}, t \cdot \frac{F_{s,s'}^{t,k}}{\sum_{k,\tilde{s}} F_{s,\tilde{s}}^{t,k}}, \quad \forall t, k, s, s'
\]

\[
d_v^{*, t} + \sum_{s \in S} [(y_{s,v}^{+t} - y_{s,v}^{-t})] = d_v^{*, t+1}, \quad \forall t, v
\]

\[
\sum_{k \in S} z_{s,k,v}^t - \sum_{k \in S} z_{k,s,v}^{t-1} = \sigma_v^t(s), \quad \forall t, s, v
\]

\[
\sum_{j \in S, v \in V} z_{s,j,v}^t \leq 1, \quad \forall t, s
\]

\[
y_{s,v}^{+t} + y_{s,v}^{-t} \leq C_v^* \cdot \sum_{i \in S} z_{i,v}^t, \quad \forall t, s, v
\]

**Maximize revenue**

**Flow preservation of bikes at stations**

**Actual flow $\propto$ Observed Flow**

**Flow preservation of vehicles in carriers**

**Enforcing right movement of carriers between stations**

**Redeployment should respect the routing strategy**
Key Idea 1: Lagrangian Dual Decomposition (LDD)

- Observation:
  - Minimal dependency between y (redeployment) and z (routing variables)

\[
\begin{align*}
\min_{y,z} & - \sum_{t,k,s,s'} R_{s,s'}^{t,k} \cdot x_{s,s'}^{t,k} + \sum_{t,v,s,s'} P_{s,s'} \cdot z_{s,s'}^{t,v} \\
\text{s.t.} & \quad d_{s}^{\#},t + \sum_{k,s} x_{s,s'}^{t-k,k} - \sum_{k,s'} x_{s,s'}^{t,k} + \sum_{v} (\hat{y}_{s,v}^{t} - \hat{y}_{s,v}^{t}) = d_{s}^{\#},t+1, \forall t, s \\
& \quad x_{s,s'}^{t,k} \leq d_{s}^{\#},t \cdot \frac{F_{s,s'}^{t,k}}{\sum_{k,s} F_{s,s'}^{t,k}}, \forall t, k, s, s' \\
& \quad d_{v}^{*,t} + \sum_{s \in S} [(\hat{y}_{s,v}^{t} - \hat{y}_{s,v}^{t})] = d_{v}^{*,t+1}, \forall t, v \\
& \quad \sum_{k \in S} z_{s,k,v}^{t} - \sum_{k \in S} z_{k,s,v}^{t-1} = \sigma_{v}^{t}(s), \forall t, s, v \\
& \quad \sum_{j \in S, v \in \mathcal{V}} z_{s,j,v}^{t} \leq 1, \forall t, s \\
& \quad \hat{y}_{s,v}^{t} + \hat{y}_{s,v}^{t} \leq C_{v}^{*} \cdot \sum_{i} z_{s,i,v}^{t}, \forall t, s, v
\end{align*}
\]
Key Idea 1: Lagrangian Dual Decomposition (LDD)

- Observation:
  - Minimal dependency between y (redeployment) and z (routing variables)

\[
\begin{align*}
\min_{y,z} & \quad - \sum_{t,k,s,s'} R_{s,s'}^{t,k} \cdot x_{s,s'}^{t,k} + \sum_{t,v,s,s'} P_{s,s'} \cdot z_{s,s'}^{t,v} \\
\text{s.t.} & \quad d_{s}^{t} + \sum_{k,s'} x_{s,s'}^{t-k,k} - \sum_{k,s} x_{s,s}^{t,k} + \\
& \quad \sum_{s,s'} (\hat{y}_{s,v}^{t} - \tilde{y}_{s,v}^{t}) = d_{s}^{t+1}, \forall t, s
\end{align*}
\]

**Redeployment**

\[
\begin{align*}
x_{s,s}^{t,k} & \leq d_{s}^{t} \cdot \frac{F_{s,s'}^{t,k}}{\sum_{k,s'} F_{s,s'}^{t,k}}, \forall t, k, s, s' \\
d_{v}^{t} + \sum_{s \in S} [(\hat{y}_{s,v}^{t} - \tilde{y}_{s,v}^{t})] = d_{v}^{t+1}, \forall t, v
\end{align*}
\]

\[
\begin{align*}
\sum_{k \in S} z_{s,k,v}^{t} - \sum_{k \in S} z_{k,s,v}^{t-1} & = o_{v}^{t}(s), \forall t, s, v \\
\sum_{j \in S, v \in V} z_{s,j,v}^{t} & \leq 1, \forall t, s \\
\hat{y}_{s,v}^{t} + \tilde{y}_{s,v}^{t} & \leq c_{v}^{*} \cdot \sum_{i} z_{s,i,v}^{t}, \forall t, s, v
\end{align*}
\]
Key Idea 1: Lagrangian Dual Decomposition (LDD)

- **Observation:**
  - Minimal dependency between y (redemption) and z (routing variables)

\[
\begin{align*}
\min_{y,z} & - \sum_{t,k,s,s'} R^{t,k}_{s,s'} \cdot x^{t,k}_{s,s'} + \sum_{t,v,s,s'} P_{s,s'} \cdot z^{t}_{s,s',v} \\
\text{s.t.} & \quad d^{\#}_{s,t} + \sum_{k,s} x^{t-k,k}_{s,s} - \sum_{k,s'} x^{t,k}_{s,s'} + \\
& \quad \sum (\tilde{y}^{t}_{s,v} - \hat{y}^{t}_{s,v}) = d^{\#}_{s,t+1}, \forall t, s \\
& \quad x^{t,k}_{s,s} \leq \frac{d^{\#}_{s,t} \cdot F^{t,k}_{s,s'}}{\sum_{s,k} F^{t,k}_{s,s'}}, \forall t, k, s, s' \\
& \quad d^{*}_{v,t} + \sum_{s \in S} [(\hat{y}^{t}_{s,v} - \tilde{y}^{t}_{s,v})] = d^{*}_{v,t+1}, \forall v, t \\
& \quad \sum_{k \in S} z^{t}_{s,k,v} - \sum_{k \in S} z^{t-1}_{k,s,v} = \sigma^{t}_{v}(s), \forall t, s, v \\
& \quad \sum_{j \in S, v} z^{t}_{s,j,v} \leq 1, \forall t, s \\
& \quad \hat{y}^{t}_{s,v} + \tilde{y}^{t}_{s,v} \leq C^{*}_{v} \cdot \sum_{i} z^{t}_{s,i,v}, \forall t, s, v 
\end{align*}
\]

\text{Redeployment}
Key Idea 1: Lagrangian Dual Decomposition (LDD)

Observation:
- Minimal dependency between y (redeployment) and z (routing variables)
- Lagrangian Dual decomposition on joint constraints
- Update price variable in the master function.

\[
\min_{y,z} \sum_{t,k,s,s'} R_{s,s'}^{t,k} \cdot x_{s,s'}^{t,k} + \sum_{t,v,s,s'} P_{s,s'}^{t} \cdot z_{s,s'}^{t},
\]

\[
\text{s.t.} \quad d_{s}^{#,t} + \sum_{k,s} x_{s,s'}^{t-k,k} - \sum_{k,s'} x_{s,s'}^{t,k} + \sum_{t,s} (\hat{y}_{s,v}^{t} - \check{y}_{s,v}^{t}) = d_{s}^{#,t+1}, \quad \forall t, s
\]

**Redeployment**

\[
x_{s,s'}^{t,k} \leq d_{s}^{#,t} \cdot \frac{F_{s,s'}^{t,k}}{\sum_{k,s} F_{s,s'}^{t,k}}, \quad \forall t, k, s, s'
\]

\[
d_{v}^{*,t} + \sum_{s \in S} [(\hat{y}_{s,v}^{t} - \check{y}_{s,v}^{t})] = d_{v}^{*,t+1}, \quad \forall t, v
\]

**Routing**

\[
\sum_{k \in S} z_{s,k,v}^{t} - \sum_{k \in S} z_{k,s,v}^{t-1} = \sigma_v^{t}(s), \quad \forall t, s, v
\]

\[
\sum_{j \in S,v \in V} z_{s,j,v}^{t} \leq 1, \quad \forall t, s
\]

\[
\hat{y}_{s,v}^{t} + \check{y}_{s,v}^{t} \leq C^* \sum_{t,v} z_{s,v}^{t}, \quad \forall t, s
\]
Key Idea 1: Lagrangian Dual Decomposition (LDD)

- **Observation:**
  - Minimal dependency between $y$ (redeployment) and $z$ (routing variables)
  - Lagrangian Dual decomposition on joint constraints
  - Update price variable in the master function.
  - Primal extraction based on routing feasibility
  - Strong upper and lower bounds

\[
\min_{y,z} \sum_{t,k,s,s'} R_{s,s'}^{t,k} \cdot x_{s,s'}^{t,k} + \sum_{t,v,s,s'} P_{s,s'}^{t} \cdot z_{s,s',v}^{t} \\
\text{s.t. } d_{s}^{\#,t} + \sum_{k,s} x_{s,s'}^{t-k,k} - \sum_{k,s'} x_{s,s'}^{t,k} + \\
\sum_{t,v,s,s'} (\hat{y}_{s,v}^{t} - \hat{y}_{s,v}^{t}) = d_{s}^{\#,t+1}, \forall t, s \\
\]

**Redeployment**

- \[x_{s,s'}^{t,k} \leq d_{s}^{\#,t} \cdot \frac{F_{s,s'}^{t,k}}{\sum_{k,s} F_{s,s'}^{t,k}}, \forall t, k, s, s'\]

- \[d_{v}^{*,t} + \sum_{s \in S} [(\hat{y}_{s,v}^{t} - \hat{y}_{s,v}^{t})] = d_{v}^{*,t+1}, \forall t, v\]

**Routing**

- \[\sum_{k \in S} z_{s,k,v}^{t} - \sum_{k \in S} z_{s,k,v}^{t-1} = \sigma_{v}^{t}(s), \forall t, s, v\]

- \[\sum_{j \in S, v \in V} z_{s,j,v}^{t} \leq 1, \forall t, s\]

- \[\hat{y}_{s,v}^{t} + \hat{y}_{s,v}^{t} - C^{*} = \sum_{i,v} z_{i,v}^{t}, \forall s, t\]
Key Idea 2: Abstraction

- Grouping of stations
  - Group base stations into abstract stations
  - Solve abstract problem using LDD
Key Idea 2: Abstraction

- Grouping of stations
  - Group base stations into abstract stations
  - Solve abstract problem using LDD
- Retrieve redeployment and routing strategy from solution to the abstract problem
  - Involves solving an optimization problem
LDD+Abstraction

Input: DRRP

Create abstract DRRP

Set dual variable $\alpha=0$

Solve abstract redeployment and routing slave

Extract primal solution

Output DRRP solution

Is Converged?

No

Update dual variable $\alpha$

Yes

Retrieve routing solution for abstract station 1

Retrieve routing solution for abstract station $n$

Retrieve redeployment policy for base stations:
pickup/drop-off allowed if a carrier present in abstract station

Output abstract DRRP solution

LDD

School of Information Systems

Supriyo Ghosh

ICAPS 06/2015
One synthetic data set and two real data sets:
- Capital Bikeshare (305 stations, 6 carriers)
- Hubway (95 stations, 4 carriers)
- Strategy of redeployment and routing for the entire day (30 minute decisions)
- Obtain strategy from part of the datasets and execute on another part

Experimental Results

- One synthetic data set and two real data sets:
  - Capital Bikeshare (305 stations, 6 carriers)
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Duality Gap less than 1% on 20 station problem
Experimental Results

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![Duality Gap less than 1% on 20 station problem](image)

![Significant improvement over CPLEX solving Global MIP](image)
Experimental Results on Real Datasets

- Comparison with current practice (abstraction + LDD)
  - Demand follows poisson with mean observed flow
  - CapitalBikeshare Data:
    - Revenue increased by 3%
    - Lost demand reduced by up to 33.76%

<table>
<thead>
<tr>
<th></th>
<th>Whole day (5am-12am)</th>
<th>Peak period (5am-12pm)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Revenue gain</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>3.47 %</td>
<td>7.74 %</td>
</tr>
<tr>
<td>Mon</td>
<td>2.33 %</td>
<td>4.48 %</td>
</tr>
<tr>
<td>Tue</td>
<td>3.07 %</td>
<td>7.86 %</td>
</tr>
<tr>
<td>Wed</td>
<td>3.30 %</td>
<td>8.95 %</td>
</tr>
<tr>
<td>Thu</td>
<td>2.86 %</td>
<td>6.04 %</td>
</tr>
<tr>
<td>Fri</td>
<td>2.51 %</td>
<td>4.50 %</td>
</tr>
<tr>
<td>Sat</td>
<td>3.87 %</td>
<td>4.33 %</td>
</tr>
<tr>
<td>Sun</td>
<td>3.01 %</td>
<td>4.04 %</td>
</tr>
<tr>
<td><strong>Lost demand reduction</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>22.72 %</td>
<td>30.58 %</td>
</tr>
<tr>
<td>Mon</td>
<td>22.46 %</td>
<td>25.55 %</td>
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<tr>
<td>Tue</td>
<td>28.56 %</td>
<td>37.10 %</td>
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<tr>
<td>Wed</td>
<td>31.16 %</td>
<td>44.88 %</td>
</tr>
<tr>
<td>Thu</td>
<td>33.76 %</td>
<td>35.97 %</td>
</tr>
<tr>
<td>Fri</td>
<td>27.37 %</td>
<td>28.15 %</td>
</tr>
<tr>
<td>Sat</td>
<td>23.61 %</td>
<td>24.30 %</td>
</tr>
<tr>
<td>Sun</td>
<td>26.00 %</td>
<td>36.51 %</td>
</tr>
</tbody>
</table>

Table 9: Revenue and lost demand comparison
Experimental Results on Real Datasets

- Comparison with current practice (abstraction + LDD)
  - Demand follows poisson with mean observed flow
  - CapitalBikeshare Data:
    - Revenue increased by 3%
    - Lost demand reduced by up to 33.76%
  - Robust to small changes in mean demand

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<tr>
<td>Sat</td>
<td>3.87 %</td>
<td>23.61 %</td>
</tr>
<tr>
<td>Sun</td>
<td>3.01 %</td>
<td>26.00 %</td>
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</tbody>
</table>
Experimental Results on Real Datasets (2)

- Hubway Data:
  - Revenue increased by 5%
  - Lost demand reduced by 60% on average

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<td>Revenue Gain (%)</td>
<td>3.94</td>
<td>5.93</td>
<td>4.45</td>
<td>5.90</td>
<td>6.27</td>
<td>2.20</td>
<td>3.15</td>
</tr>
<tr>
<td>Lost Demand Reduction(%)</td>
<td>42.6</td>
<td>60.7</td>
<td>58.5</td>
<td>54.7</td>
<td>77.2</td>
<td>69.8</td>
<td>74.0</td>
</tr>
</tbody>
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Experimental Results on Real Datasets (2)

- Hubway Data:
  - Revenue increased by 5%
  - Lost demand reduced by 60% on average
- Better matching of demand and supply
  - Ideally all the points should lie on the identity line

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Matching without redeployment

Matching using our redeployment
Summary

- Dynamic redeployment of bikes
- Important large-scale problem with relevance to many cities
- Two techniques (Decomposition, Abstraction) to improve scalability and provide near-optimal solutions
- Reduces lost demand by over 20% on both datasets
- Robust to small changes in demand
Questions???

supriyog.2013@phdis.smu.edu.sg
References


