Online Learning, Social Values and Ethical Issues in Manufacturing and Services Operations Management

INTERNATIONAL WORKSHOP ON INTERNET-PLUS MANUFACTURING AND SERVICES OPERATIONS MANAGEMENT

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Today’s talk

Topics on considering social values, ethical issues, and online learning in dynamic and complex operations management and decision-making environments.

• Achieving Social Fairness in an online resource allocations to individuals/groups (Chen, Li, Sun, Y 2021)

• Dynamically learning client Behavior/Preference/Utility in computing fair market equilibrium prices with incomplete market information (Jalota, Y 2021)

• Balance Data Privacy and Prediction Accuracy/Efficiency in Statistical Learning (Zhu, Y 2021)

• Industrial Cases (Cardinal Operations)
Online Resource Allocation & Revenue Management

- m type of resources; T customers
- Decision maker needs to decide whether and how much resources are allocated to each customer
- Resources are limited!
- **Online setting:**
  - Customers arrive sequentially and the decision needs to be made instantly upon the customer arrival

\[
\begin{align*}
\text{max} & \quad \sum_{t=1}^{T} r_t x_t \\
\text{s.t.} & \quad \sum_{t=1}^{T} a_{it} x_t \leq b_i, \quad i = 1, \ldots, m \\
& \quad 0 \leq x_t \leq 1 \quad \text{or} \quad x_t \in \{0, 1\}, \quad t = 1, \ldots, T
\end{align*}
\]
Customer-Type Based LP formulation

In the original offline LP formulation, $x_t$ represents the decision for the $t$-th customer, $a_t$ represents the request vector of the $t$-th customer, and $r_t$ represents the reward of the $t$-th customer.

$$\max \sum_{t=1}^{T} r_t x_t \quad \text{s.t.} \quad \sum_{t=1}^{T} a_t x_t \leq b, \quad x_t \in [0, 1]$$

In the customer-type based formulation, there are in total $J$ types of customers. The $j$-th type arrives with a probability $p_j$ (proportion of type $j$ but unknown); the request vector and reward of the $j$-th type customer is $c_j$ and $\mu_j$.

$$\max \sum_{j=1}^{J} p_j \mu_j y_j \quad \text{s.t.} \quad \sum_{j=1}^{J} p_j c_j y_j \leq b / T, \quad y_j \in [0, 1]$$

The decision variable $y_j$ represents the fraction/probability of $j$-th type customer being accepted. But, in real applications, most LPs have nonunique solutions…
A Motivation Example

- Consider an allocation problem: there exists three types of orders/customers, where the first two types have the reward/resource characteristics that are considered equivalent from the system.

- The following plots show the acceptance fraction/probability of the three types across time by two different online algorithms: the simplex and interior-point methods (Jasin 2015, Chen et al 2021).
Fairness Desiderata

- **Individual Fairness**: Similar customers should be treated similarly. For certain customer types, there exist multiple optimal allocation rules. Unfortunately, the optimal object value depends on the total resources spent, not on the resources spent on which groups. Therefore, some individual or group may be ignored by the online algorithm/allocation-rule.

- **Time Fairness**: The algorithm may tend to accept mainly the first half (or the second half of the orders), which is unfair or unideal such
Fair Optimal Solution for Offline Problem

\[
\max \sum_{j=1}^{J} p_j \mu_j y_j \quad \text{s.t.} \quad \sum_{j=1}^{J} p_j c_j y_j \leq b / T, \quad y_j \in [0, 1]
\]

- We define \( y^* \) the fair offline optimal solution of the LP problem as the analytical center of the optimal solution set, which represents an “average” of all the corner optimal solutions.
- The fair solution \( y^* \) will treat individuals fairly, based on their similar reward and resource consumption.
- An online learning algorithm would use the data points up to time \( t \) and solve the sample-based linear program to decide \( y_t \).
Performance Measure

- Let $y_t$ be the allocation rule at time $t$ which encodes the accepting probabilities under the online algorithm $\pi$. Then we define the cumulative unfairness of the online algorithm $\pi$ as

$$UF_T(\pi) = E[\sum_{t=1}^{T} |y_t - y^*|^2]$$

- Intuition: If $UF_T(\pi)$ is sub-linear, we know Time Fairness is satisfied since the deviation of the online solution cannot be large. Moreover, Individual Fairness is satisfied because we know $UF_T(\pi)$ being sub-linear implies $y_t$ converging to $y^*$.

- Let $j_t$ denote the incoming customer type at time $t$, the Revenue Regret is defined as

$$Reg_T(\pi) = E[\sum_{t=1}^{T} r_t (y^*_j - y_{t,j})]$$

Regret measures the performance loss compared to the optimal policy.
Our Result

- We develop an algorithm [Chen, Li & Y (2021)] that achieve
  \[ UF_T(\pi) = O(\log T) \]
  \[ Reg_T(\pi) \text{ Bounded w.r.t } T \]

- Key ideas in algorithm design:
  - At each time \( t \), we use interior-point method to obtain the sample analytic-center solution and randomly make decision based on sample solution \( y_t \).
  - We also adjust the right-hand-side resource of the LP to ensure the depletion of binding resources and non-binding resources does not affect the fairness.
The Online Algorithm can be Extended to Bandits with Knapsack (BwK) Applications

• For the previous problem, the decision maker first observe the customer order and then decide whether to accept it or not.

• An alternative setting is that the decision maker first decides which order/arm (s)he may accept/pull, and then receive a random resource consumption vector $a_j$ and yield a random reward $\pi_j$ of the pulled arm.

• Known as the Bandits with Knapsacks, and it is a tradeoff exploration v.s. exploitation.
The decision variable \( x_j \) represents the total-times of pulling the j-th arm.

We have developed a two-phase algorithm

- **Phase I**: Distinguish the optimal super-basic variables/arms from the optimal non-basic variables/arms with as fewer number of plays as possible
- **Phase II**: Use the arms in the optimal face to exhaust the resource through an adaptive procedure and achieve fairness

The algorithm achieves a problem dependent regret that bears a logarithmic dependence on the horizon \( T \). Also, it identifies a number of LP-related parameters as the bottleneck or condition-numbers for the problem

- Minimum non-zero reduced cost
- Minimum singular-values of the optimal basis matrix.

**First algorithm** to achieve the \( O(\log T) \) regret bound

Takeaway: **Stochastic data are learnable and certain social fairness is achievable for online linear programming**
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• Balance Data Privacy and Prediction Accuracy/Efficiency in Statistical Learning

• Industrial Cases (Cardinal Operations)
Monetary pricing instruments have served as a primary mechanism to achieve an efficient and fair allocation of resources.

Goods are priced to match supply and demand.

Users with the highest willingness to pay receive the goods.
However, there are many settings when monetary transfers are disallowed such as **Public Goods**

- **Public Goods Allocation**
- **University Researchers sharing a common computing resource**
- **Vaccine Distribution**
This has led to a growing interest in the use of Artificial Currencies to mediate the allocation of resources/goods.

$p_j$ : Price of Good $j$

$w_i$ : Budget of Agent $i$
A canonical model studied in artificial-currency-based resource allocation is that of **Fisher Markets**

\[ u_{ij} : \text{Preference of Agent } i \text{ for one unit of good } j \]
\[ x_{ij} : \text{Quantity of good } j \text{ purchased by person } i \]
\[ p_j : \text{Price of Good } j \]
\[ w_i : \text{Budget of Agent } i \]

**Individual Optimization Problem:**

\[
\max_{\mathbf{x}_i} \sum_{j} u_{ij} x_{ij} \\
\text{s.t. } p^T \mathbf{x}_i \leq w_i \\
\mathbf{x}_i \geq 0
\]

\( M = \text{Total Number of Goods} \)
Classical Fisher Markets provide a fair framework to derive prices through a centralized optimization problem.

Individual Optimization Problem:

\[
\begin{align*}
\max_{x_i} & \quad \sum_j u_{ij} x_{ij} \\
\text{s.t.} & \quad p^T x_i \leq w_i \\
& \quad x_i \geq 0
\end{align*}
\]

Social Optimization Problem:

\[
\begin{align*}
\max_{x_i, \forall i \in [N]} & \quad \sum_i w_i \log \left( \sum_j u_{ij} x_{ij} \right) \\
\text{s.t.} & \quad \sum_i x_{ij} = \bar{s}_j, \forall j \in [M] \\
& \quad x_{ij} \geq 0, \forall i, j
\end{align*}
\]

$p_j$ : Price of Good $j$ = Dual Variable of Constraint $j$
However, the centralized Fisher market needs the “Complete Individual/Private utility Information”

Individual Optimization Problem:

$$\max_{x_i} \sum_j u_{ij} x_{ij}$$

s.t. $p^T x_i \leq w_i$

$x_i \geq 0$

Social Optimization Problem:

$$\max_{x_i, \forall i \in [N]} \sum_i w_i \log \left( \sum_j u_{ij} x_{ij} \right)$$

s.t. $\sum_i x_{ij} = \bar{s}_j, \forall j \in [M]$  

$x_{ij} \geq 0, \forall i, j$

$p_j : \text{Price of Good } j = \text{Dual Variable of Constraint } j$

Capacity Constraints
We now study an online and privacy-protecting variant of Fisher markets with Incomplete-Information and develop Learning Algorithms with sub-linear regret guarantees.

Buyers arrive sequentially with utility and budget parameters drawn as 
\[(w, u) \overset{i.i.d.}{\sim} P\]

Convergence of the optimal price vector of the dual problem

Online Algorithms with sub-linear regret and constraint violation guarantees
We evaluate the performance of our algorithms through their regret and violation of capacity constraints.

**Regret (Optimality Gap)**

\[ R_n(\pi) = \sum_i w_i \log \left( \sum_j u_{ij} x_{ij}^* \right) - \sum_i w_i \log \left( \sum_j u_{ij} x_{ij}(\pi) \right) \]

- **Optimal Offline Objective**
- **Objective of online policy**

**Constraint Violation**

**Norm of the violation of capacity constraints of the online policy** \( \pi \)

\[ V_j(\pi) = \sum_j x_{ij}(\pi) - \bar{s}_j \]

Violation of Capacity Constraint of good \( j \)

**Norm of the expected constraint violation**

\[ V_n(\pi) = \| \mathbb{E}[V(\pi)] \|_2 \]
We establish convergence of the optimal dual prices

**Main Result 1:** The optimal dual solution $\mathbf{p}_n^*$ of the SAA problem converges to the optimal solution $\mathbf{p}^*$ of the stochastic program with rate $O\left(\frac{1}{\sqrt{n}}\right)$. 

**Dual of social optimization problem with dual of the capacity constraints $p_j$**

$$
\min_{\mathbf{p}} \sum_{t=1}^{n} w_t \log(w_t) - \sum_{t=1}^{n} w_t \log\left(\min_{j=1}^{m} \frac{p_j}{u_{tj}}\right) + \sum_{j=1}^{m} p_j \bar{s}_j - \sum_{t=1}^{n} w_t
$$

**Equivalent Sample Average Approximation (SAA) of Dual Problem**

$$
\min_{\mathbf{p}} D_n(\mathbf{p}) = \sum_{j=1}^{m} p_j \bar{s}_j + \frac{1}{n} \sum_{t=1}^{n} \left( w_t \log(w_t) - w_t \log\left(\min_{j \in [m]} \frac{p_j}{u_{tj}}\right) - w_t \right)
$$

**Dual Stochastic Program**

$$
\min_{\mathbf{p}} D(\mathbf{p}) = \sum_{j=1}^{m} p_j d_j + \mathbb{E}\left[\left( w \log(w) - w \log\left(\min_{j \in [m]} \frac{p_j}{u_j}\right) - w \right)\right]
$$
We obtain sub-linear regret and constraint violation guarantees under different informational assumptions

**Known Probability Distribution**

User parameters \((w, u)\) are revealed

**Privacy Preserving**

Algorithm 1: Set price based on solution of Stochastic Program

Algorithm 2: Set prices based on a sequence of dual problems using revealed parameters

Algorithm 3: Update and post prices through gradient descent on dual problem and observe buying behavior, which reduces to tatonnement

Main Result 2: Under each of the above informational assumptions the above dual based algorithms achieve expected regret \(R_n(\pi) \leq O(\sqrt{n})\) and the expected constraint violation \(V_n \leq O(\sqrt{n})\), where \(n\) is the number of arriving users.
The numerical results indicate superior performance relative to the theoretical guarantees.
Takeaway: it is possible to develop online algorithm for solving the Fisher market of good-allocation with sub-linear regret guarantees while keeping certain customer “privacy”

Buyers arrive sequentially with utility and budget parameters drawn as

Convergence of the optimal price vector of the dual problem

Online Algorithms with sub-linear regret and constraint violation guarantees
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- Achieving Social Fairness in an online resource allocations to individuals/groups
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- **Balance Data Privacy and Prediction Accuracy/Efficiency in Statistical Learning**
- Industrial Cases (Cardinal Operations)
Statistical Learning and Regression Across Decentralized Data Centers

- **Decentralized Learning**: Method that learns or trains an algorithm across multiple decentralized centers holding local data.

- **Pros**: Such method protects data privacy and data security.

- **Cons**: Many decentralized learning algorithms suffers from slow convergence and solution quality.
Statistical Learning Model

• Each center $i$ possess model data matrix $X_i \in R^{s \times p}$ and dependent variable vector $y_i \in R^{s \times 1}$.

• Let $(x_{i,j}, y_{i,j})$ be the $j^{th}$ data pair of the $i^{th}$ data center.

• The decision maker tries to find the \textbf{global estimator} $\beta \in R^{p \times 1}$ that minimizes a \textbf{regression error}

\[ \sum_{i=1}^{b} \sum_{j=1}^{s} f((x_{i,j}, y_{i,j}); \beta) \]

where $f((x_{i,j}, y_{i,j}); \beta)$ represent the \textbf{loss function}. 
Commonly Used Loss Functions

• Commonly used loss function are **convex** in $\beta$, including
  - Least Square
    \[ f((x, y); \beta) = ||x\beta - y||_2^2 \]
  - Ridge
    \[ f((x, y); \beta) = ||x\beta - y||_2^2 + \alpha ||\beta||_2^2 \]
  - Lasso
    \[ f((x, y); \beta) = ||x\beta - y||_2^2 + \alpha ||\beta||_1 \]
  - Elastic Net
    \[ f((x, y); \beta) = ||x\beta - y||_2^2 + \alpha ||\beta||_1 + (1 - \alpha) ||\beta||_2^2 \]
  - Logistic
    \[ f((x, y); \beta) = \log(1 - \exp(-yx\beta)) \]
Statistical Learning Across Decentralized Data Centers

- Centralized Learning
  - All local data are uploaded to one server

- Decentralized Learning
  - Local data cannot be exchanged

Decision Maker Receives
\[ X = [X1; X2; X3] \]
\[ Y = [y1; y2; y3] \]
And trains in one server

Decision Maker trains local data in local servers, pools the training results and aggregates the results without accessing data.
Optimization Methods in Decentralized Learning

- Gradient or Conjugate-Gradient Descend (SGD) in minimizing
  \[ \sum_{i=1}^{b} \sum_{j=1}^{s} f((x_{i,j}, y_{i,j}); \beta) \]

- Consensus/distributed Alternating Direction Method of Multipliers (ADMM, essentially a dual gradient method)
  - Introducing local estimators \( \beta_i \) to each center and reformulate the problem as
    \[ \sum_{i=1}^{b} \sum_{j=1}^{s} f((x_{i,j}, y_{i,j}); \beta_i) \]
    \[ \text{s.t.} \quad \beta_i - \beta = 0 \quad \forall \ i = 1, \ldots, b \]
  - Let \( \lambda_i \) be the dual with respect to the constraint \( \beta_i - \beta = 0 \) , and \( \rho_p \) be the step-size to the primal consensus ADMM, the augmented Lagrangian is given by
    \[ L(\beta_i, \beta, \lambda_i) = \sum_{i=1}^{b} \sum_{j=1}^{s} f((x_{i,j}, y_{i,j}); \beta_i) + \sum_{i=1}^{b} \lambda_i^T (\beta_i - \beta) + \sum_{i=1}^{b} \frac{\rho_p}{2} (\beta_i - \beta)^T (\beta_i - \beta) \]
Balancing Privacy and Efficiency

• The complete decentralized and privacy-protecting algorithms are typically slow in convergence

• We now designing ADMM algorithm with data exchange that balance the trade-off between privacy and efficiency
  • Introducing Dual Randomly-Assembled Cyclic ADMM (DRC-ADMM)
  • Data exchange is necessary – comparison with variants Randomly-Permuted ADMM and Cyclic ADMM.

• Numerical Results
Dual Randomly-Assembled Cyclic ADMM

Data Center 1
\( (x_{1,1}, y_{1,1}), (x_{1,2}, y_{1,2}), (x_{1,3}, y_{1,3}); \)
Local data

Data Center 2
\( (x_{2,1}, y_{2,1}), (x_{2,2}, y_{2,2}), (x_{2,3}, y_{2,3}); \)
Local data

Data Center 3
\( (x_{3,1}, y_{3,1}), (x_{3,2}, y_{3,2}), (x_{3,3}, y_{3,3}); \)
Local data

Global Data Pool
Introducing Dual Randomly-Assembled Cyclic ADMM

Data Center 1

$((x_{1,1}, y_{1,1}), (x_{1,2}, y_{1,2}))$

Local data

Cyclic updating

Data Center 2

$((x_{2,1}, y_{2,1}), (x_{2,3}, y_{2,3}))$

Local data

Cyclic updating

Data Center 3

$((x_{3,2}, y_{3,2}), (x_{3,3}, y_{3,3}))$

Local data

Global Data Pool

$((x_{1,3}, y_{1,3}), (x_{2,2}, y_{2,2}), (x_{3,1}, y_{3,1}))$
Data Exchange is Beneficial in **Linear Regression**

- If each the time we directly add all global data to each of the block (here the data structure at each block is **fixed**), and compare
  - Distributed ADMM with global data
  - Cyclic ADMM with global data
  - Randomly Permuted ADMM with global data

<table>
<thead>
<tr>
<th>Algorithms</th>
<th>Run Time (s)</th>
<th>Number of Iterations</th>
<th>Absolute Loss</th>
</tr>
</thead>
<tbody>
<tr>
<td>Primal Consensus ADMM</td>
<td>100</td>
<td>1,520,752</td>
<td>$3.60 \times 10^{-3}$</td>
</tr>
<tr>
<td>Primal Consensus ADMM (with global data)</td>
<td>100</td>
<td>1,627,174</td>
<td>$3.51 \times 10^{-1}$</td>
</tr>
<tr>
<td>Cyclic ADMM (with global data)</td>
<td>100</td>
<td>1,124,016</td>
<td>$2.62 \times 10^{-1}$</td>
</tr>
<tr>
<td>RP ADMM (with global data)</td>
<td>100</td>
<td>1,103,549</td>
<td>$3.04 \times 10^{-1}$</td>
</tr>
<tr>
<td>DRC-ADMM</td>
<td>100</td>
<td>4153</td>
<td>$4.56 \times 10^{-9}$</td>
</tr>
</tbody>
</table>
## Numerical Results on UCI ML Regression Repository I

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Primal distributed</th>
<th>DRC-ADMM</th>
<th>Fix run time = 100 s</th>
<th>Primal distributed</th>
<th>DRC-ADMM</th>
<th>Fix number of iteration = 200</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bias Correction</td>
<td>$1.60 \times 10^{-3}$</td>
<td>$3.71 \times 10^{-10}$</td>
<td></td>
<td>$3.20 \times 10^{-3}$</td>
<td>$6.31 \times 10^{-7}$</td>
<td></td>
</tr>
<tr>
<td>Bike Sharing Beijing</td>
<td>$8.43 \times 10^{-4}$</td>
<td>$9.57 \times 10^{-12}$</td>
<td></td>
<td>$2.03 \times 10^{-2}$</td>
<td>$6.61 \times 10^{-6}$</td>
<td></td>
</tr>
<tr>
<td>Bike Sharing Seoul</td>
<td>$2.60 \times 10^{-3}$</td>
<td>$1.71 \times 10^{-8}$</td>
<td></td>
<td>$8.87 \times 10^{0}$</td>
<td>$5.80 \times 10^{-3}$</td>
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</tr>
<tr>
<td>Wine Quality Red</td>
<td>$3.45 \times 10^{-15}$</td>
<td>$2.31 \times 10^{-14}$</td>
<td></td>
<td>$8.10 \times 10^{-3}$</td>
<td>$1.22 \times 10^{-7}$</td>
<td></td>
</tr>
<tr>
<td>Wine Quality White</td>
<td>$7.36 \times 10^{-15}$</td>
<td>$1.24 \times 10^{-13}$</td>
<td></td>
<td>$2.40 \times 10^{-3}$</td>
<td>$1.56 \times 10^{-6}$</td>
<td></td>
</tr>
<tr>
<td>Appliance Energy</td>
<td>$5.02 \times 10^{-12}$</td>
<td>$1.61 \times 10^{-9}$</td>
<td></td>
<td>$7.56 \times 10^{-1}$</td>
<td>$4.77 \times 10^{-5}$</td>
<td></td>
</tr>
<tr>
<td>Online News Popularity *</td>
<td>$9.42 \times 10^{-16}$</td>
<td>$3.23 \times 10^{-15}$</td>
<td></td>
<td>$7.70 \times 10^{-4}$</td>
<td>$4.63 \times 10^{-8}$</td>
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</tr>
<tr>
<td>Portugal 2019 Election *</td>
<td>$3.97 \times 10^{-16}$</td>
<td>$4.97 \times 10^{-14}$</td>
<td></td>
<td>$3.22 \times 10^{-5}$</td>
<td>$1.99 \times 10^{-10}$</td>
<td></td>
</tr>
<tr>
<td>Relative Location of CT</td>
<td>$1.65 \times 10^{-13}$</td>
<td>$6.44 \times 10^{-12}$</td>
<td></td>
<td>$1.29 \times 10^{0}$</td>
<td>$4.79 \times 10^{-4}$</td>
<td></td>
</tr>
<tr>
<td>SEGMM GPU</td>
<td>$2.63 \times 10^{-13}$</td>
<td>$2.20 \times 10^{-13}$</td>
<td></td>
<td>$4.60 \times 10^{-3}$</td>
<td>$2.65 \times 10^{-6}$</td>
<td></td>
</tr>
<tr>
<td>Superconductivity Data</td>
<td>$1.25 \times 10^{-1}$</td>
<td>$2.98 \times 10^{-6}$</td>
<td></td>
<td>$6.97 \times 10^{-1}$</td>
<td>$4.99 \times 10^{-4}$</td>
<td></td>
</tr>
<tr>
<td>UJIIndoorLoc Data</td>
<td>$3.76 \times 10^{-1}$</td>
<td>$4.48 \times 10^{-8}$</td>
<td></td>
<td>$8.45 \times 10^{-1}$</td>
<td>$2.53 \times 10^{-2}$</td>
<td></td>
</tr>
<tr>
<td>Wave Energy Converters</td>
<td>$3.40 \times 10^{-3}$</td>
<td>$7.12 \times 10^{-10}$</td>
<td></td>
<td>$7.70 \times 10^{-3}$</td>
<td>$2.39 \times 10^{-7}$</td>
<td></td>
</tr>
<tr>
<td>Year Prediction MSD</td>
<td>$3.60 \times 10^{-3}$</td>
<td>$4.56 \times 10^{-9}$</td>
<td></td>
<td>$3.91 \times 10^{-2}$</td>
<td>$2.64 \times 10^{-5}$</td>
<td></td>
</tr>
</tbody>
</table>

* The covariance matrix’s spectrum is of $10^{20}$, which is hard for all algorithms to converge. We further scale each entry by $\sqrt{n}$. 

35
Numerical Results on UCI ML Regression Repository II

- With 5% of access to global data, DRC ADMM utilizes the benefit of data exchange, and outperforms primal distributed ADMM.

- Benefit of DRC-ADMM
  - Manage to get a good quality of solution within fewer iteration, which further reduces the communication load across centers
  - Manage to get a good quality of solution within a fixed time.
Previous literature suggests that distributed ADMM method suffers from slow convergence in classification problems (1).

Numerical results suggest that, DRC-ADMM with data sharing could again overcome the slow convergence issue.

The numerical data for logistic regression is provided by Stanford Medicine with number of observations $n = 2,000$ and feature dimensionality $p = 26$. We compare the objective value under each algorithm – with smaller objective value, the algorithm performs better.

Applications of Data Sharing in **Logistic Regression II**

- Although distributed ADMM suffers from slow convergence compared with traditional Newton’s method that requires full access of data, DRC-ADMM with data sharing could outperform traditional algorithms with only **limited access to the data**.

<table>
<thead>
<tr>
<th>Algorithms</th>
<th>Number of Iterations</th>
<th>Objective Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Centralized Optimization via Newton’s Method (2)</td>
<td>50</td>
<td>$2.15 \times 10^{-2}$</td>
</tr>
<tr>
<td>Multi-block Primal Consensus ADMM</td>
<td>50</td>
<td>$8.53 \times 10^{-2}$</td>
</tr>
<tr>
<td>Multi-block DRC-ADMM (5% data sharing)</td>
<td>50</td>
<td>$2.22 \times 10^{-3}$</td>
</tr>
<tr>
<td>Multi-block DRC-ADMM (10% data sharing)</td>
<td>50</td>
<td>$1.01 \times 10^{-3}$</td>
</tr>
<tr>
<td>Multi-block DRC-ADMM (20% data sharing)</td>
<td>50</td>
<td>$5.67 \times 10^{-4}$</td>
</tr>
</tbody>
</table>


Data Sharing in Conjugate Gradient Method

- Data sharing could also be applied in helping **preconditioning** for **conjugate gradient method**. Specifically, we use the global data pool to build a good pre-conditioning matrix.

- In UCI ML regression repository Year Prediction MSD, preconditioning under data sharing helps convergence. We report number of iteration required to the target tolerance (3).

<table>
<thead>
<tr>
<th>Algorithms</th>
<th>Target Tolerance $10^{-6}$</th>
<th>Target Tolerance $10^{-10}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>CG without preconditioning</td>
<td>564</td>
<td>1,112</td>
</tr>
<tr>
<td>CG with preconditioning (1% data sharing)</td>
<td>6</td>
<td>10</td>
</tr>
<tr>
<td>CG with preconditioning (5% data sharing)</td>
<td>4</td>
<td>7</td>
</tr>
<tr>
<td>CG with preconditioning (10% data sharing)</td>
<td>3</td>
<td>6</td>
</tr>
</tbody>
</table>

**Takeaway:** It is better to share even a small amount data among different groups/parties to combat global issues.

(3) tolerance is defined by $\|b - Ax\| / \|b\|$. https://www.mathworks.com/help/matlab/ref/cgs.html
Today’s talk

Topics on considering social values, ethical issues, and online learning in dynamic and complex operations management and decision-making environments.

- Achieving Social Fairness in an online resource allocations to individuals/groups
- Dynamically learning client Behavior/Preference/Utility in computing fair market equilibrium prices with incomplete market information
- Balance Data Privacy and Prediction Accuracy/Efficiency in Statistical Learning
- Industrial Cases (Cardinal Operations)
Case I: About For-U

Make road freight transportation simpler and smarter

FOR-U chose to work with intermediaries in the transport sector so that drivers can get orders via agents and conventional intermediaries can get more orders.

FOR-U sent operation team to monitor each deal to avoid possible corruption problem between shipper representative and drivers, which bought true value for its clients and marked its core competence was the offline operation ability.
What Need to be Improved Originally

On the shipper side of the equation: finding carriers can be a cumbersome and inefficient process. Freight rates are volatile and lack transparency. Lack of services and dispatch delays are prevalent during loading and shipment. En-route order tracking remains limited, and cost settlement suffers from a lack of standardization and significant risk.

On the carrier side: drivers often experience difficulties identifying legitimate loads. They are also hurt by volatile and nontransparent freight rates. Transport capacity is often undercut by inefficient utilization, and issues such as a lack of payment guarantees and protracted payment periods plague the settlement process.

Connect dots and routes to improve efficiency
Reduce empty-loaded rate and disruptive incidences
Guarantee safe and timely freight delivery
How We Address the Problem

Real-time Truck Scheduling

• The traditional truck scheduling model restricts each truck to given routes, which may cause too many stops for the truck, e.g. truck can only stand wait for orders but not to seek orders within its searching area.

• An effective algorithm is required to break the conventional scheduling rules in order to reduce the stop rate, improve the driving efficiency, while considering the constraints, like time window, empty driving mileage, vehicle resources and special situations.

Multi-objective Optimization

- Minimize empty driving mileage
- Maximize the number of assigned orders
- Dynamically adjust searching area
- Predict future orders of each district
- Globally optimize the whole network

Complex Business Scenarios

- Different truck types and order types should be considered in the model to support the specific business scenario
- Balance the monthly driving mileage of each truck
- Intelligently arrange driver break to avoid fatigue driving
- A simulation system is built to simulate different special situations in the real world, e.g. order cancellation, vehicle accident

Humanism 人性化
Seasonality 季节性
Fairness 公平性
What We Did for For-U - Truck Scheduling System

Application 1: Real-time Scheduling

Real-time scheduling system is used to efficiently assign trucks with real-time input orders in order to optimize monthly profit and monthly truck efficiency (minimize empty driving rate, stop rate), satisfying all the business constraints.

Application 2: Route Quotation System

The simulation system with the core of scheduling algorithm is used to calculate the impact of each bidding route on the whole network, including the change of monthly profit and monthly truck efficiency (empty driving rate, stop rate). Based on the evaluation, a proper price is given to each route.

Application 3: Decision on the Number of Trucks

Whenever the order pool is changed, e.g. the number of orders in one month is increased from 10,000 to 12,000, the simulation system is used to decide how many new trucks are supposed to be added in the network.

Application 4: Decision on the Number of Orders

Whenever the truck pool is changed, e.g. truck driver quit his job, the simulation system is used to decide how many orders are supposed to be added or removed from the network.
Improvements and Results

Before
Two-sides/Three-sides

After
Globally optimize the whole network

China's First Successful Case of using Intelligent Scheduling System to Solve Trunk Vehicle Transportation

Growth in the Profit

- Original Profit
- Profit after Optimization
- Including Financial Profit

Winning Rate of the Bid

- 10% → 60%
  More than 50 Competitive Suppliers

Reduce Empty-Loaded Rate

- 2.1%
### Algorithm Design

<table>
<thead>
<tr>
<th>Model</th>
<th>Description</th>
</tr>
</thead>
</table>
| \[
\max_{\{x_{ij}^k, y_i^k\}} \sum_{k \in K} \sum_{i \in I} \left( y_i^k - \sum_{j \in D, j \neq i} \left( \delta_{ij} \sum_{k \in K} x_{ij}^k \right) \right) \\
\text{subject to} \sum_{k \in K} y_i^k \leq 1, \forall i \in I \cup D \]
| Vehicle Routing Problem |
| \[
x_{ii}^k = 0, \forall i \in I, k \in K \]
| Simulated Annealing |
| \[
x_{ij}^k = 0, \forall i \in I^O, j \in D^O, k \in K \]
| Differential Evolution |
| \[
\sum_{j \in D^O} x_{ij}^k \leq y_i^k, \forall i \in I^O, k \in K \]
| Variable Neighborhood Search |
| \[
\sum_{j \in I^O} x_{ij}^k = y_i^k, \forall i \in I, k \in K \]

### Problem Scale

300 trucks X 12,000 orders

Over 10 billion decision variables commercial solver UNABLE To Solve customized algorithm Solved in Minutes

**Takeaway:** Considering social responsibility and humanity, together with operation optimizing, benefit companies greatly.
Case II: Carbon Emission Process Control

Carbon Emission in the Industry

Carbon emission in industry represent 23 percent of greenhouse gas emissions (2019). Greenhouse gas emissions from industry primarily come from burning fossil fuels for energy, as well as greenhouse gas emissions from certain chemical reactions necessary to produce goods from raw materials.
### Market conditions of fertilizer industry

Excess capacity, severe similarity and Low-Level competition are forcing fertilizer enterprises to giving impetus to industrial transformation.

### Problems in transformation and coping strategy in supply chain:

<table>
<thead>
<tr>
<th>Problem</th>
<th>Change</th>
<th>Solution</th>
<th>Target</th>
</tr>
</thead>
<tbody>
<tr>
<td>Excess capacity</td>
<td>S&amp;OP</td>
<td>S&amp;OP: 1. Producing a fit product to making maximized profit in fit time by operation research 2. Sales forecasting, analyzing the limit of material and capacity, overall planning to storage network, adjustment plan in minutes, cost reduction in production, storage and transportation</td>
<td>Improve S&amp;OP skill</td>
</tr>
<tr>
<td>Vast consignment</td>
<td>New marketing model</td>
<td></td>
<td>Improve response speed to the market</td>
</tr>
<tr>
<td>Severe similarity</td>
<td>New system of products</td>
<td></td>
<td>Improve the output-input ratio</td>
</tr>
<tr>
<td>Control of energy</td>
<td>Sophisticated management</td>
<td>Build the KPI system of supply chain management</td>
<td>Improve sophisticated management skill</td>
</tr>
</tbody>
</table>

**Liuguo Chemical Industry S&OP—Background**
**Liuguo-Shanshu S&OP Engine**

**Shanshu S&OP engine strengthen LIUGUO Chemical Industry supply chain**

**Demand Plan**
- Market demand analysis
- Real-time monitor of demand
- Intelligentized advice of demand plan

**Sales area**
- Sales forecast
- Sales forecast
- Salesman

**Sales forecast**
- Sales director
- Sales Department

**Production Plan**
- S&OP meeting
- Factory

**Production Plan**
- Capacity estimate
- Production priority
- Multi-factory cooperation

**Production Plan & Delivery Plan**
- Demand Plan & Delivery Plan
- Inventory Status

**Overall planning to storage network**
- Goods calling based on demand
- Intelligentized allocating advice

**Supplying Plan**
- Storage
- Product
- Dealer Client

**Strengthen:**
- Experience -> System evaluation
- Off-line -> On-line
- Serial plan -> Closed loop plan
- Save 5% transportation cost (allocating transportation).
- Reduce 20% inventories, save 20 million cost of storage.
- Reduce 50% time of human resource in demand plan and production plan.
Mathematical Programming Model:
minimize the total operation cost & total amount of carbon emission

Minimize production cost + inventory cost + transportation cost + carbon expenditure

Subject to:

(Delivery) \[ \delta_{i,t+1} = \delta_{i,t} + D_{i,t} - \sum_p d_{ipt} \]

(Inventory) \[ n_{i,t+1} = n_{i,t} - d_{ipt} + x_{ipt} - \sum_{\mu_{ji}>0} \mu_{ji} x_{jpt} + \sum_{p'} y_{ip'pt} - \sum_{p'} y_{ipp't} \]

(Capacity) \[ \sum_i \alpha_{ip} x_{ipt} \leq C_p \]

(Carbon control) carbon bound \[ \geq \sum_{i,p,t} \text{emission} \]

(Operation rules) Many more ...

Minimize the total amount of carbon emission in the supply chain

All supplier's and OEM's emission of are taken into consideration as the flow decision of the model.
Intelligentize S&OP function description – S&OP simulation

**S&OP Definition**

- Demand schedule forecast
- Real order
- Inventory
- Purchasing order
- Resource capacity

**S&OP**

**S&OP Decision content**

- How to satisfy the sales demand to the maximum extent?
- How to organize production (production type, quantity) with higher profit?
- How to select external customer sales order when it is excess production capacity?
- Choose which orders the company has maximum profit when the production capacity is limited?
- Choose which orders the company has maximum profit when the material is limited?

**S&OP Method**

**Input**

- Sales order, sales forecast, unit capacity, in-route inventory, inventory...
- Different sales strategy
- Different capacity (resource utilization rate)
- Different shift and work time
- Different purchasing plan
- Other input

**Output**

- Fluctuation and influence of the production, sales, inventory and supply plan, because of the change of multiple parameter
- The production plan, sales plan and inventory plan guided on S&OP
- Sales qty, production qty, inventory plan and purchasing plan based on this version's production and operation plan
- Cost and profit based on this version's production and operation plan
- KPI comparison of different plan versions
Control/Visualization Tower of the Supply Chain with the Consideration of Carbon Emission
Liuguo Chemical Industry sales and operation planning - Implementation achievement

**Materials**
- Production Data Monitoring
- Production optimization continuously
- Material efficiency improvement about 15%

**Production**
- Multiple line\multiple remodel type, production scheduling with integration of the production capacity, order and inventory information, Improve the effective capacity utilization 20%
- Via more effective planning of capacity and production schedule, reduce operations like melted, reduce energy consumption (Carbon emission index) about 10%

**Operation**
- Inventory cost reduce 18 Millions
- Customer satisfaction rate improve 15%

**Industry Chain**
- Augment the customer satisfaction rate in the market
- Improvement the company sales and operation planning capacity
- Release the production delicacy management of company
- Release the interconnection of whole company’s core operation data
- Insure the gross profit rate
- Improve the stability of supply chain

**Takeaway:** It is possible to improve profitability and reduce carbon emission at the same time, if …
Thank You!