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.

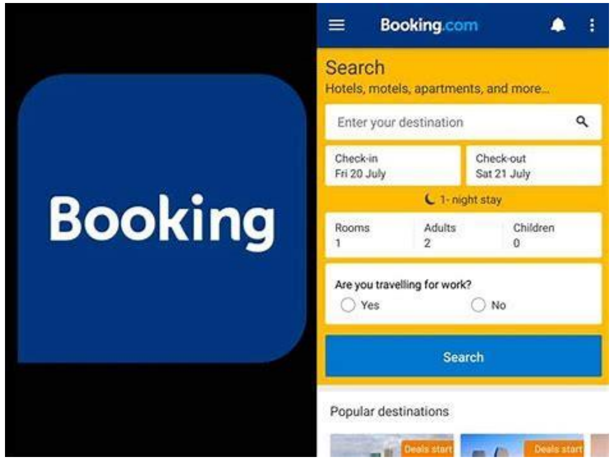
- **Achieving Social Fairness in an online resource allocations to individuals/groups (Chen, Li, Sun, Y 2021)**

- **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

$$\max \sum_{t=1}^{T} r_t x_t$$

$$\text{s.t.} \sum_{t=1}^{T} a_{it} x_t \le b_i, \quad i = 1, \ldots, m$$

$$0 \le x_t \le 1 \ \text{ or } \ x_t \in \{0, 1\}, \quad t = 1, \ldots, T$$

Customer-Type Based LP formulation

In the original offline LP formulation, x_t represents the decision for the t-th customer, $\mathbf{a}_t$ represents the request vector of the t-th customer, and r_t represents the reward of the t-th customer

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

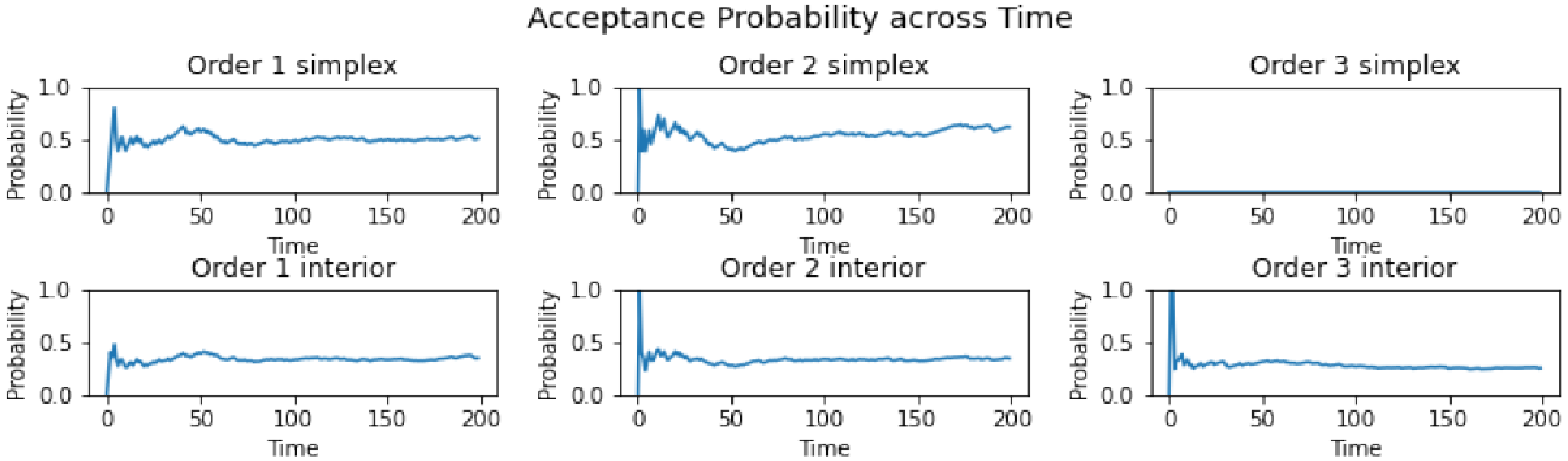
In the customer-type based formulation, there are in total J types of customers. The j-th type arrives with a probability p_j (proportion of type j but unknown); the request vector and reward of the j-th type customer is $\boldsymbol{c}_j$ and μ_j

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

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 $\boldsymbol{y}^*$ 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 $\boldsymbol{y}^*$ 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 $\boldsymbol{y}_t$.

Performance Measure

- Let $\boldsymbol{y}_t$ be the allocation rule at time t which encodes the accepting probabilities under the online algorithm π. Then we define the cumulative unfairness of the online algorithm π as

$$UF_T(\pi) = E[\sum_{t=1}^{T} ||\boldsymbol{y}_t - \boldsymbol{y}^*||_2^2]$$

- 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 $\boldsymbol{y}_t$ converging to $\boldsymbol{y}^*$.
- Let j_t denote the incoming customer type at time t, the Revenue Regret is defined as
- $$\mathrm{Reg}_T(\pi) = E[\sum_{t=1}^{T} r_t(y_{j_t}^* - y_{t,j_t})]$$

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 $\boldsymbol{y}_t$.
  - 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 $\mathbf{a}_j$ and yield a random reward π_j of the pulled arm.
- Known as the Bandits with Knapsacks, and it is a tradeoff exploration v.s. exploitation

$$\max \quad \sum \pi_j x_j \quad \text{s.t.} \quad \sum_j \boldsymbol{a}_j x_j \le \boldsymbol{b}\,, \quad x_j \quad \ge 0 \qquad \forall\ j = 1, \ldots, J$$

- 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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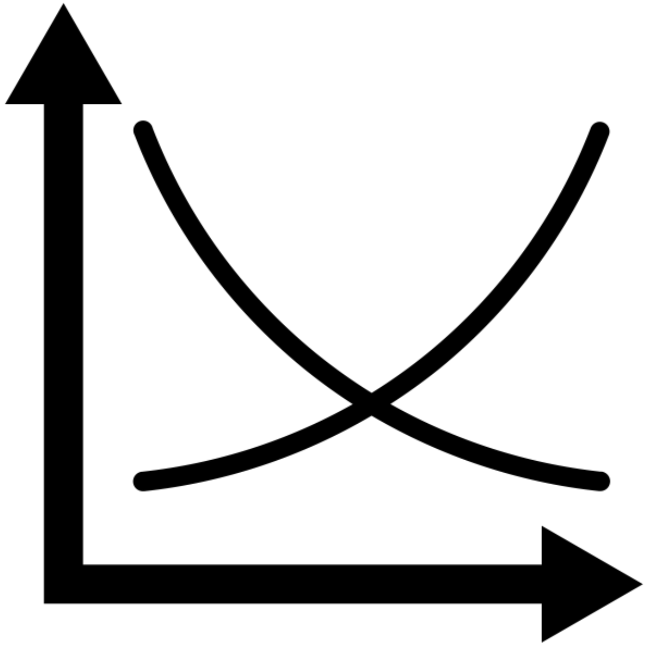
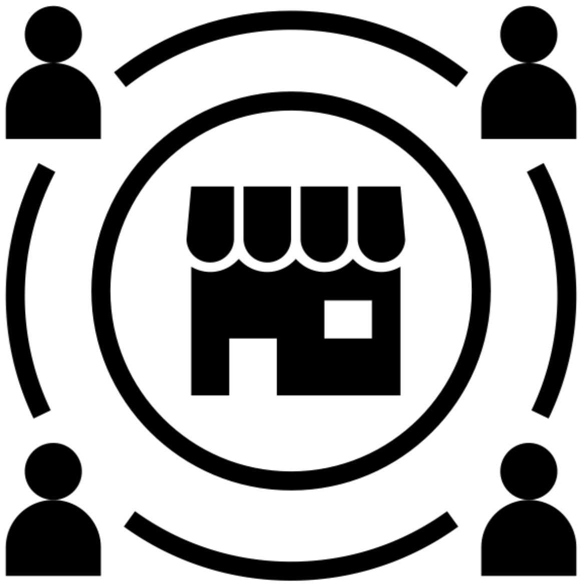
- **Industrial Cases (Cardinal Operations)**

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

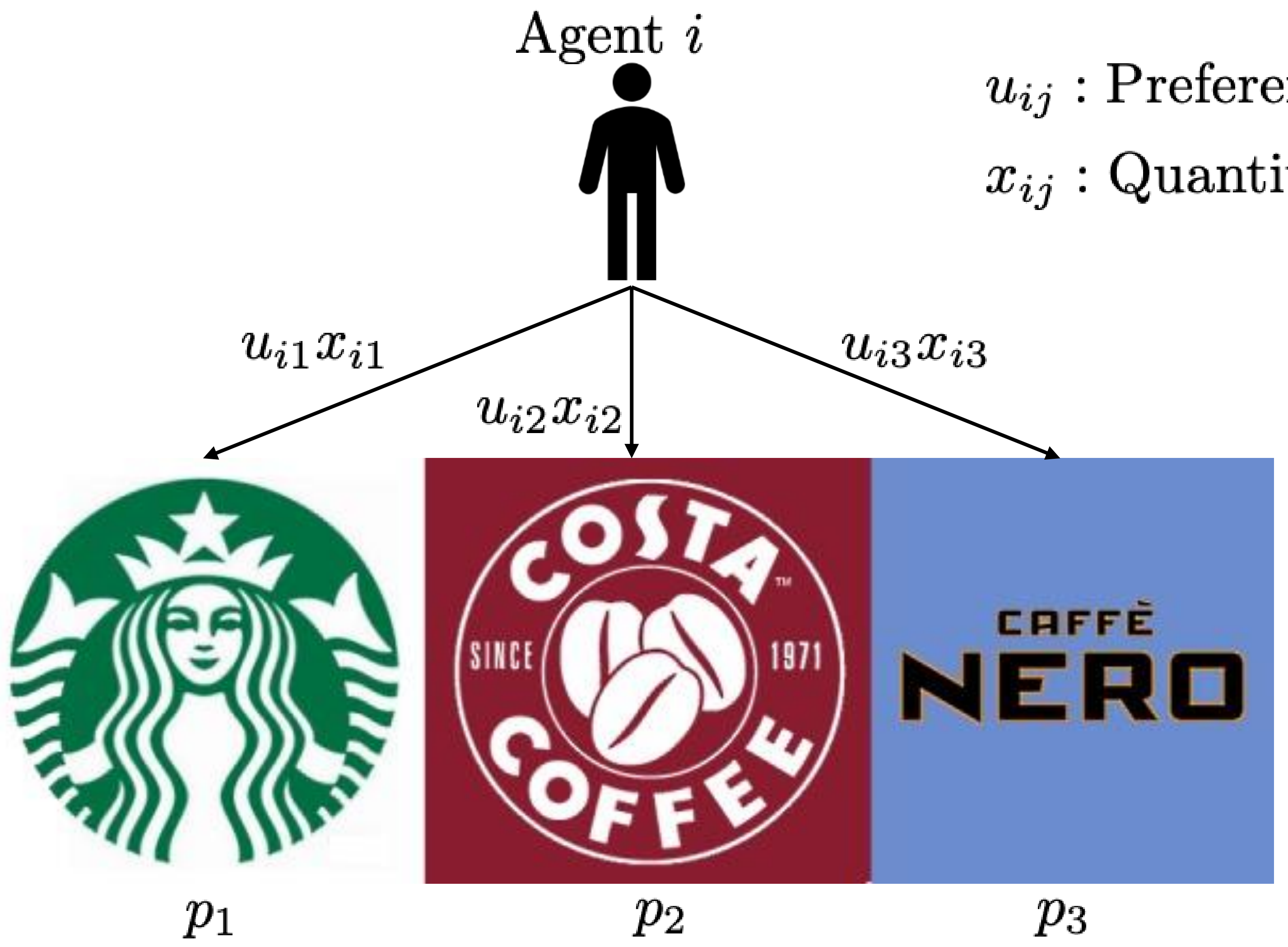
Artificial Currency

p_j : Price of Good j

Budget Endowment

w_i : Budget of Agent i

A canonical model studied in artificial-currency-based resource allocation is that of Fisher Markets



$M =$ Total Number of Goods

u_{ij} : Preference of Agent i for one unit of good j

x_{ij} : Quantity of good j purchased by person i

p_j : Price of Good j

w_i : Budget of Agent i

Individual Optimization Problem:

$$\max_{\mathbf{x}_i} \sum_j u_{ij} x_{ij}$$

$$\text{s.t. } \mathbf{p}^T \mathbf{x}_i \leq w_i$$

$$\mathbf{x}_i \geq \mathbf{0}$$

Classical Fisher Markets provide a **fair** framework to derive prices through a centralized optimization problem

Individual Optimization Problem:

$$\max_{\mathbf{x}_i} \sum_j u_{ij} x_{ij}$$

$$\text{s.t.} \;\; \mathbf{p}^T \mathbf{x}_i \leq w_i$$

$$\mathbf{x}_i \geq \mathbf{0}$$

$$\Longleftrightarrow$$

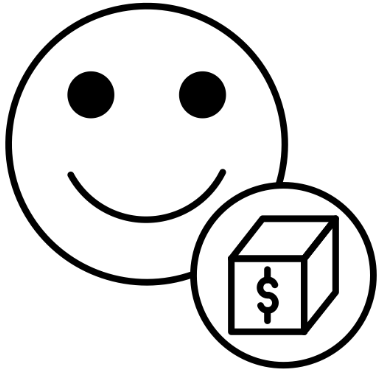
Social Optimization Problem:

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

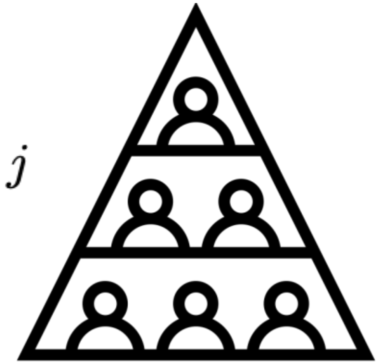
$$\text{s.t.} \;\; \boxed{\sum_i x_{ij} = \bar{s}_j, \forall j \in [M]}$$

Capacity Constraints

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



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:

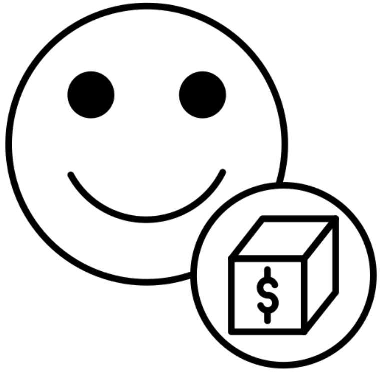
$$\max_{\mathbf{x}_i} \sum_j u_{ij} x_{ij}$$
$$\text{s.t. } \mathbf{p}^T \mathbf{x}_i \leq w_i$$
$$\mathbf{x}_i \geq \mathbf{0}$$

$\Longleftrightarrow$

Social Optimization Problem:

$$\max_{\mathbf{x}_i, \forall i \in [N]} \sum_i w_i \log \left(\sum_j u_{ij} x_{ij} \right)$$
$$\text{s.t. } \boxed{\sum_i x_{ij} = \bar{s}_j, \forall j \in [M]}$$
$$x_{ij} \geq 0, \forall i, j$$

Capacity Constraints



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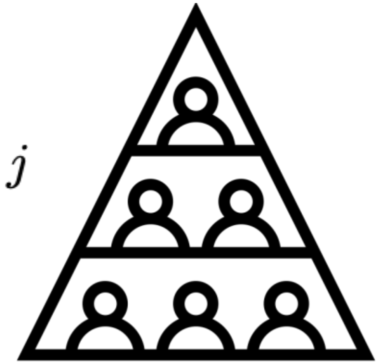
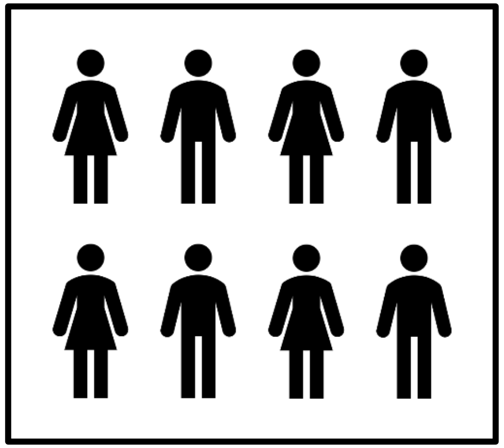
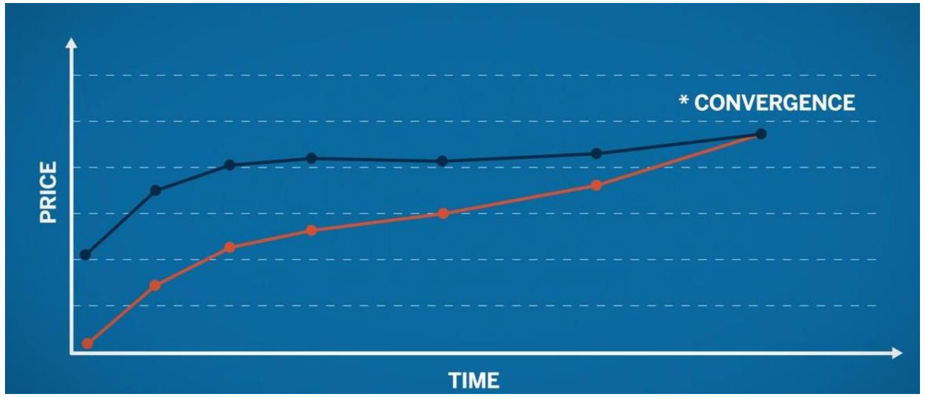
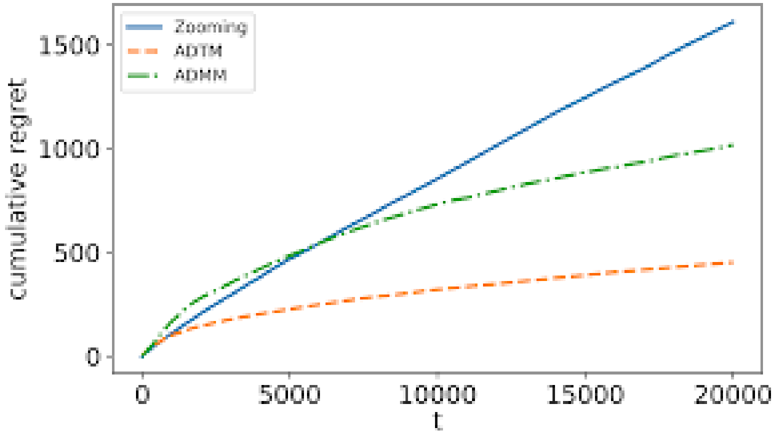


We now study an online and privacy-protecting variant of Fisher markets with Incomplete-Information and develop Learning Algorithms with sub-linear regret guarantees







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

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)

Difference in the Optimal Social Objective of the online policy $\boldsymbol{\pi}$ to that of the optimal offline solution

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

Optimal Offline Objective

Objective of online policy

Constraint Violation

Norm of the violation of capacity constraints of the online policy $\boldsymbol{\pi}$

$$\boxed{V_j(\pi) = \sum_j x_{ij}(\boldsymbol{\pi}) - \bar{s}_j}$$

Violation of Capacity Constraint of good j

$$\boxed{V_n(\boldsymbol{\pi}) = ||\mathbb{E}[V(\boldsymbol{\pi})]||_2}$$

Norm of the expected constraint violation

We establish convergence of the optimal dual prices

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

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

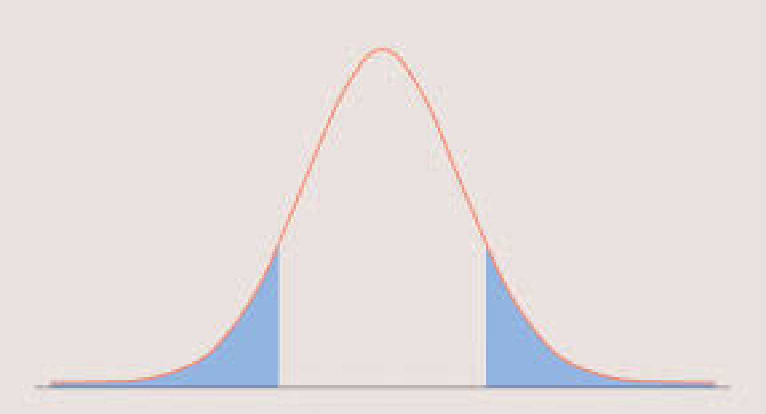
Dual Stochastic Program

$$\min_{\mathbf{p}} D(\mathbf{p}) = \sum_{j=1}^{m} p_j d_j + \mathbb{E}\left[\left(w \log(w) - w \log\left(\min_{j\in[m]} \frac{p_j}{u_j}\right) - w \right)\right]$$

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

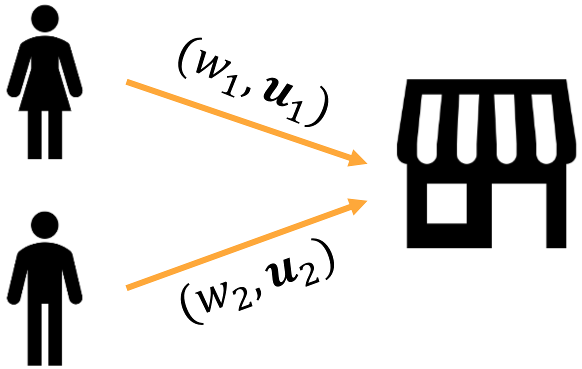
We obtain sub-linear regret and constraint violation guarantees under different informational assumptions

Known Probability Distribution



Algorithm 1: Set price based on solution of Stochastic Program

User parameters $(w, \boldsymbol{u})$ are revealed



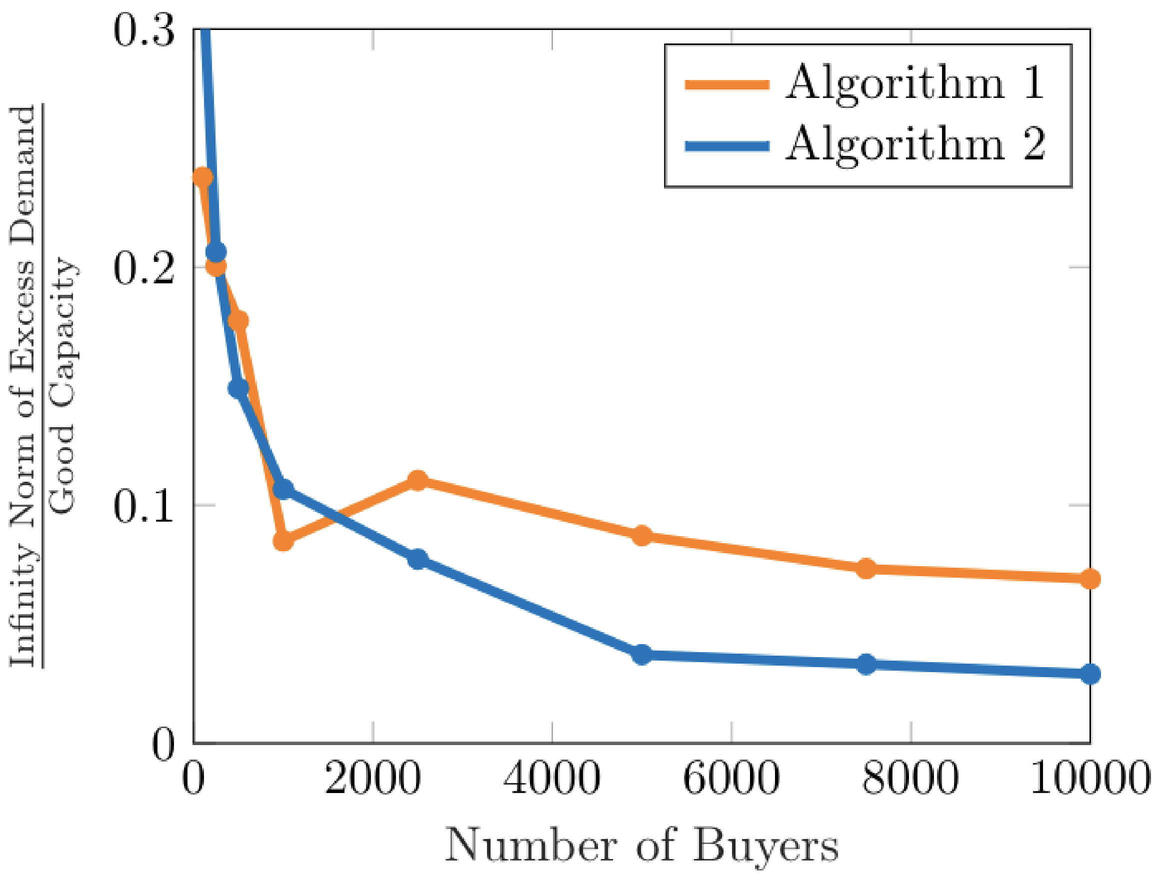
Algorithm 2: Set prices based on a sequence of dual problems using revealed parameters

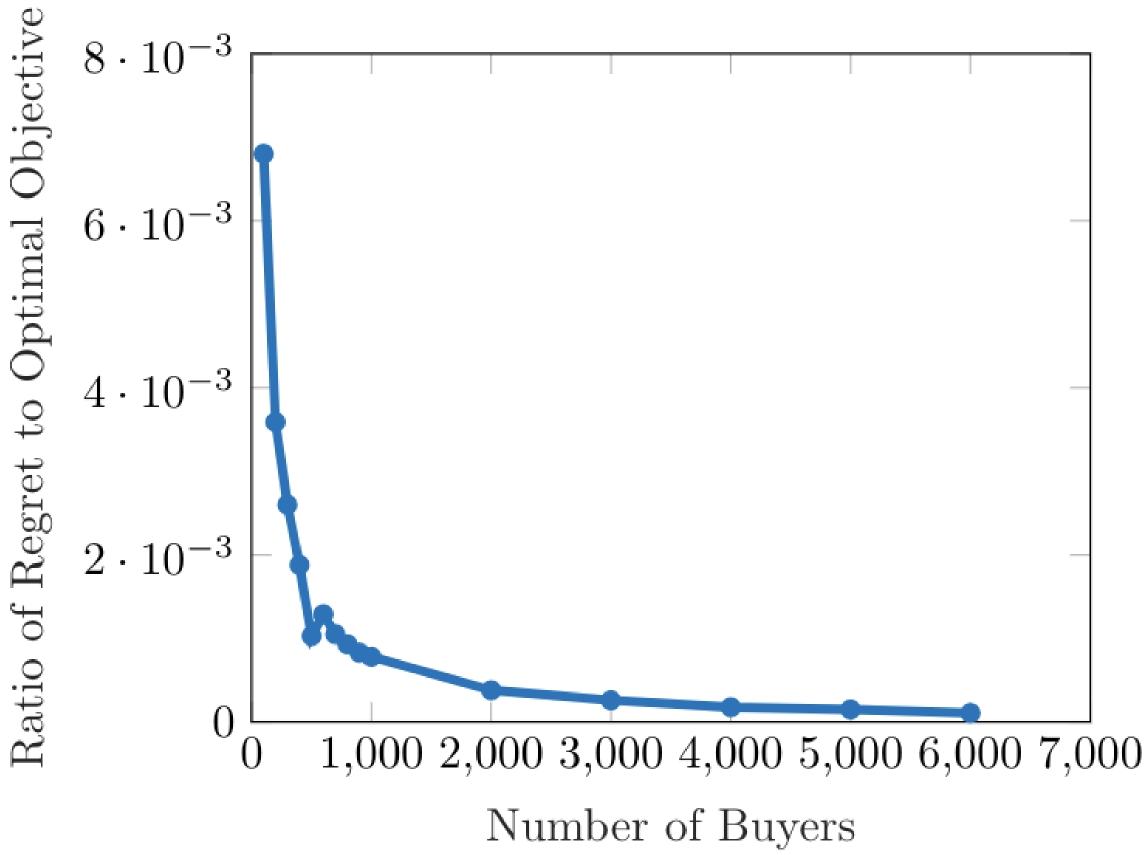
Privacy Preserving

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

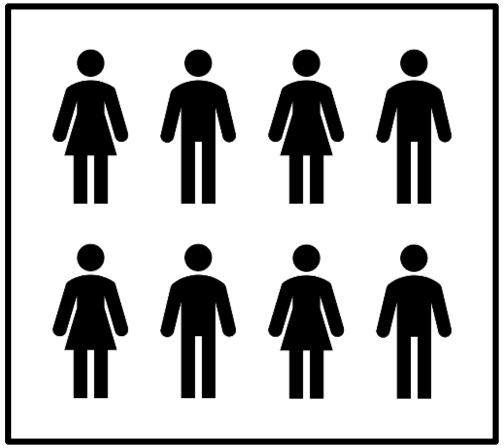
Main Result 2: Under each of the above informational assumptions the above dual based algorithms achieve expected regret $R_n(\boldsymbol{\pi}) \leq O(\sqrt{n})$ and the expected constraint violation $V_n \leq O(\sqrt{n})$, where n is the number of arriving users.

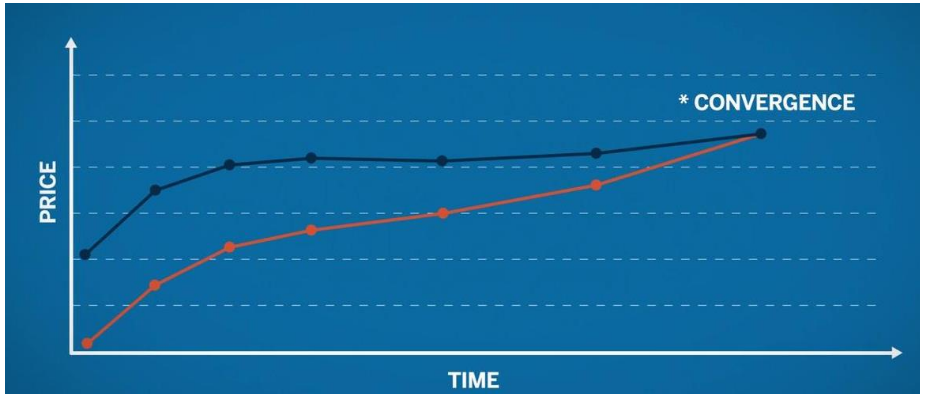
The numerical results indicate superior performance relative to the theoretical guarantees

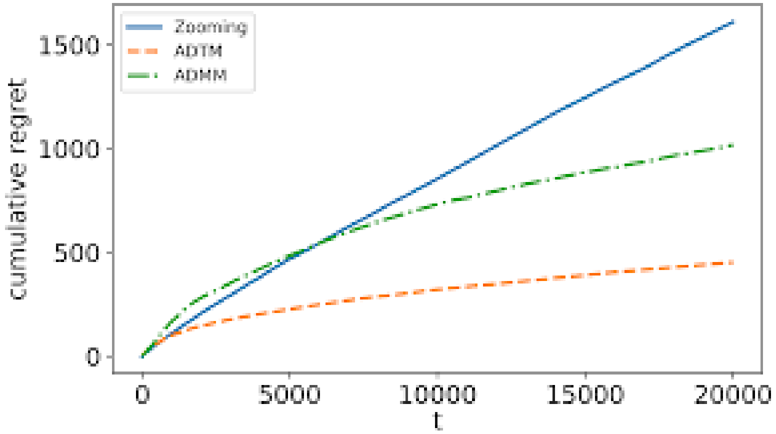




Takeaway: it is possible to develop online algorithm for solving the Fisher market of good-allocation with sub-linear regret guarantees while keeping certain customer “privacy”







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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** $\boldsymbol{X}_i \in R^{s \times p}$ and **dependent variable** vector $\boldsymbol{y}_i \in R^{s \times 1}$.

- Let $\left(\boldsymbol{x}_{i,j}, y_{i,j}\right)$ be the j^{th} data pair of the i^{th} data **center.**

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

$$\sum_{i=1}^{b} \sum_{j=1}^{s} f\left((\boldsymbol{x}_{i,j}, y_{i,j}); \boldsymbol{\beta}\right)$$

where $f\left((\boldsymbol{x}_{i,j}, y_{i,j}); \boldsymbol{\beta}\right)$ represent the **loss function**.

Commonly Used Loss Functions

- Commonly used loss function are **convex** in $\boldsymbol{\beta}$, including
  - Least Square

    $$f((\boldsymbol{x}, \boldsymbol{y}); \boldsymbol{\beta}) = ||\boldsymbol{x}\boldsymbol{\beta} - y||_2^2$$

  - Ridge

    $$f((\boldsymbol{x}, \boldsymbol{y}); \boldsymbol{\beta}) = ||\boldsymbol{x}\boldsymbol{\beta} - y||_2^2 + \alpha||\boldsymbol{\beta}||_2^2$$

  - Lasso

    $$f((\boldsymbol{x}, \boldsymbol{y}); \boldsymbol{\beta}) = ||\boldsymbol{x}\boldsymbol{\beta} - y||_2^2 + \alpha||\boldsymbol{\beta}||_1$$

  - Elastic Net

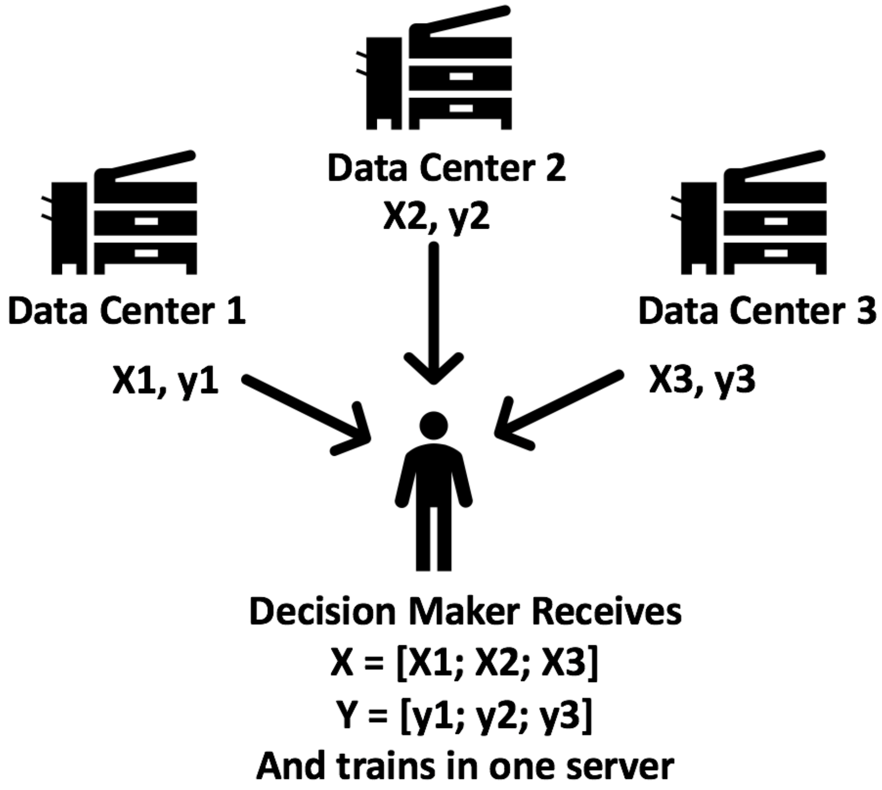
    $$f((\boldsymbol{x}, \boldsymbol{y}); \boldsymbol{\beta}) = ||\boldsymbol{x}\boldsymbol{\beta} - \boldsymbol{y}||_2^2 + \alpha||\boldsymbol{\beta}||_1 + (1 - \alpha)\ ||\boldsymbol{\beta}||_2^2$$

  - Logistic

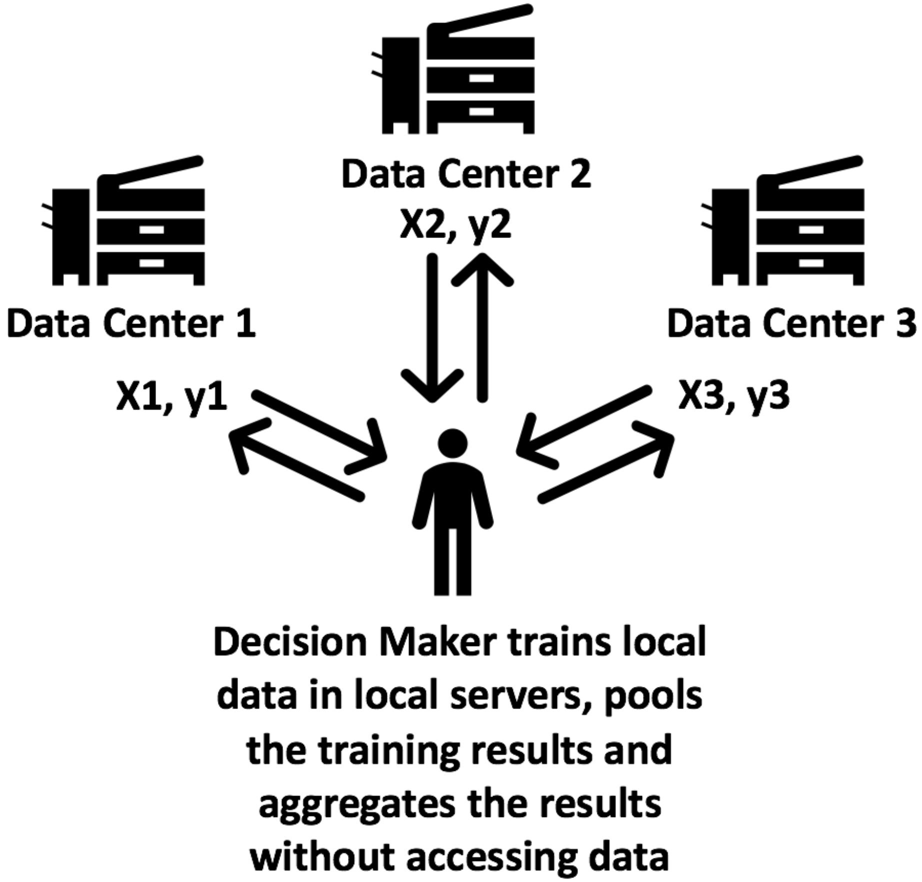
    $$f((\boldsymbol{x}, \boldsymbol{y}); \boldsymbol{\beta}) = log(1 - exp(-y\boldsymbol{x}\boldsymbol{\beta}))$$

Statistical Learning Across Decentralized Data Centers

- Centralized Learning
- All local data are uploaded to one



- Decentralized Learning
- Local data cannot be exchanged



Optimization Methods in Decentralized Learning

- Gradient or Conjugate-Gradient Descend (SGD) in minimizing

$$\Sigma_{i=1}^{b} \Sigma_{j=1}^{s} f\left((\boldsymbol{x}_{i,j}, y_{i,j}); \boldsymbol{\beta}\right)$$

- Consensus/distributed Alternating Direction Method of Multipliers (ADMM, essentially a dual gradient method)
  - Introducing **local estimators** $\boldsymbol{\beta}_i$ to each center and reformulate the problem as

$$\sum_{i=1}^{b} \sum_{j=1}^{s} f((\mathbf{x}_{i,j}, y_{i,j}); \boldsymbol{\beta}_i)$$

$$s.t. \quad \boldsymbol{\beta}_i - \boldsymbol{\beta} = 0 \quad \forall\, i = 1, \ldots, b$$

  - Let λ_i be the dual with respect to the constraint $\boldsymbol{\beta}_i - \boldsymbol{\beta} = \mathbf{0}$, and ρ_p be the step-size to the primal consensus ADMM, the augmented Lagrangian is given by

$$L(\boldsymbol{\beta}_i, \boldsymbol{\beta}, \boldsymbol{\lambda}_i) = \sum_{i=1}^{b} \sum_{j=1}^{s} f((\mathbf{x}_{i,j}, y_{i,j}); \boldsymbol{\beta}_i) + \sum_{i=1}^{b} \boldsymbol{\lambda}_j^T (\boldsymbol{\beta}_i - \boldsymbol{\beta}) + \sum_{i=1}^{b} \frac{\rho_p}{2} (\boldsymbol{\beta}_i - \boldsymbol{\beta})^T (\boldsymbol{\beta}_i - \boldsymbol{\beta})$$

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

$(\boldsymbol{x}_{1,1}, y_{1,1}), (\boldsymbol{x}_{1,2}, y_{1,2}), (\boldsymbol{x}_{1,3}, y_{1,3});$

Local data

Data Center 2

$(\boldsymbol{x}_{2,1}, y_{2,1}), (\boldsymbol{x}_{2,2}, y_{2,2}), (\boldsymbol{x}_{2,3}, y_{2,3});$

Local data

Data Center 3

$(\boldsymbol{x}_{3,1}, y_{3,1}), (\boldsymbol{x}_{3,2}, y_{3,2}), (\boldsymbol{x}_{3,3}, y_{3,3});$

Local data

Global Data Pool

Introducing Dual Randomly-Assembled Cyclic ADMM

Data Center 1

$(\boldsymbol{x}_{1,1}, y_{1,1}), (\boldsymbol{x}_{1,2}, y_{1,2}),$

Local data

Data Center 2

$(\boldsymbol{x}_{2,1}, y_{2,1}),$ $(\boldsymbol{x}_{2,3}, y_{2,3});$

Local data

Data Center 3

$(\boldsymbol{x}_{3,2}, y_{3,2}), (\boldsymbol{x}_{3,3}, y_{3,3});$

Local data

Cyclic updating

Cyclic updating

Global Data Pool

$(\boldsymbol{x}_{1,3}, y_{1,3});$ $(\boldsymbol{x}_{2,2}, y_{2,2}),$ $(\boldsymbol{x}_{3,1}, y_{3,1}),$

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

Algorithms	Run Time (s)	Number of Iterations	Absolute Loss
Primal Consensus ADMM	100	1,520,752	3.60×10^{-3}
Primal Consensus ADMM (with global data)	100	1,627,174	3.51×10^{-1}
Cyclic ADMM (with global data)	100	1,124,016	2.62×10^{-1}
RP ADMM (with global data)	100	1,103,549	3.04×10^{-1}
DRC-ADMM	100	4153	4.56×10^{-9}

Numerical Results on UCI ML Regression Repository I

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

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

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**.

Applications of Data Sharing in Logistic Regression I

- 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 calue, the algorithm performs better.

(1) Gopal, Siddharth, and Yiming Yang. "Distributed training of large-scale logistic models." *International Conference on Machine Learning*. PMLR, 2013.

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**.

Algorithms	Number of Iterations	Objective Value
Centralized Optimization via Newton's Method (2)	50	2.15×10^{-2}
Multi-block Primal Consensus ADMM	50	8.53×10^{-2}
Multi-block DRC-ADMM (5% data sharing)	50	2.22×10^{-3}
Multi-block DRC-ADMM (10% data sharing)	50	1.01×10^{-3}
Multi-block DRC-ADMM (20% data sharing)	50	5.67×10^{-4}

(2) https://web.stanford.edu/~boyd/papers/admm/logreg-l1/logreg.html
Boyd, Stephen, Neal Parikh, and Eric Chu. Distributed optimization and statistical learning via the alternating direction method of multipliers. Now Publishers Inc, 2011. c

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).

Algorithms	Target Tolerance 10^{-6}	Target Tolerance 10^{-10}
CG without preconditioning	564	1,112
CG with preconditioning (1% data sharing)	6	10
CG with preconditioning (5% data sharing)	4	7
CG with preconditioning (10% data sharing)	3	6

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

FOR-U SMART FREIGHT

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.

Shipper

Book a truck at your fingertips

Efficiency / Transparency / Reliability

Carrier

More earnings with dignity

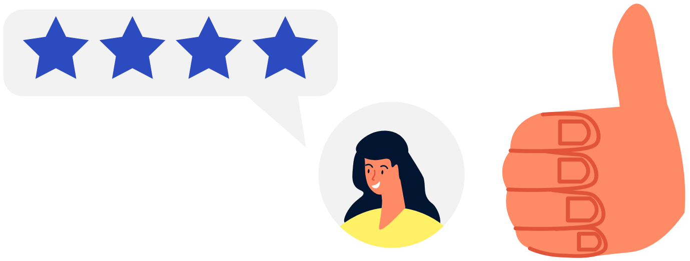
Real jobs / Fast payment / Haggle-free

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	Complex Business Scenarios
■ **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**	■ 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.

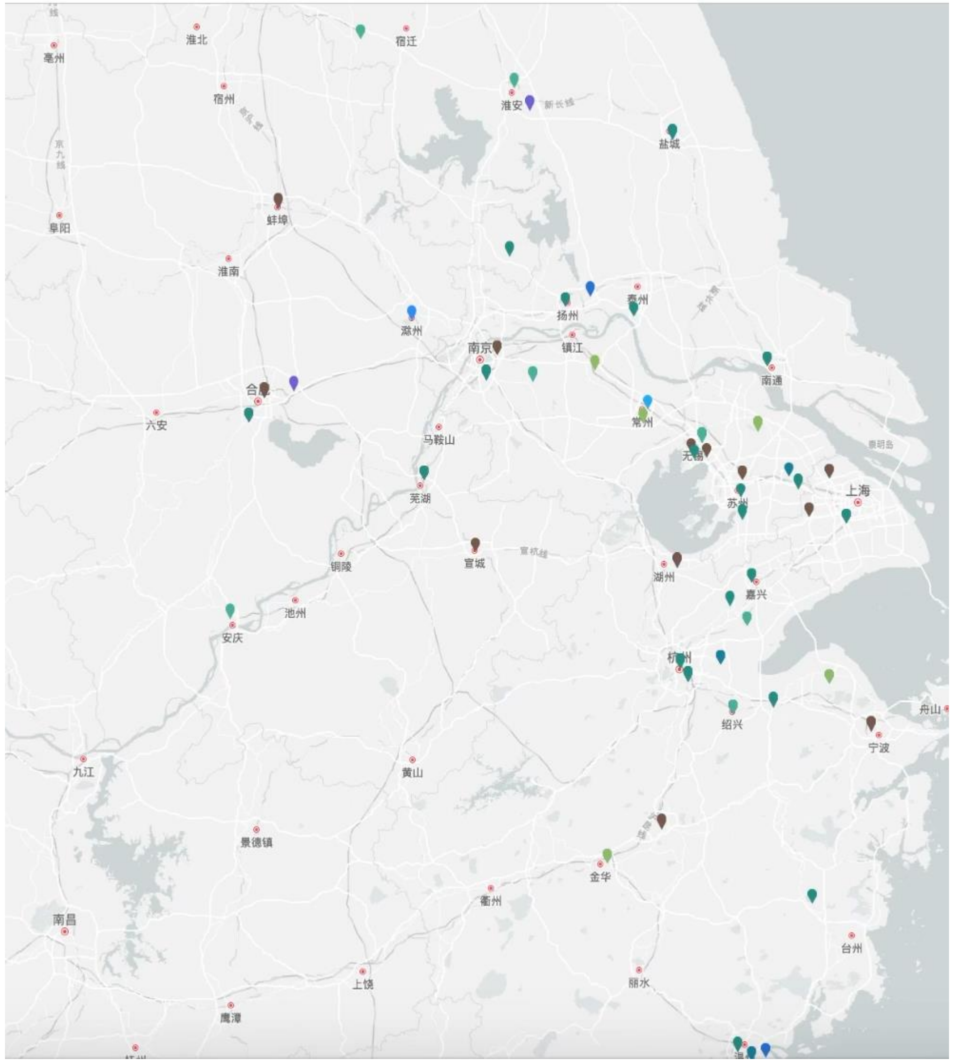
Improvements and Results

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

Winning Rate of the Bid

10% → **60%**

More than 50 Competitive Suppliers

Reduce Empty-Loaded Rate

2.1%

Algorithm Design

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Model

$$\max_{\{x_{ij}^k, y_i^k, t_i\}} \sum_{k\in\mathcal{K}}\sum_{i\in\mathcal{I}}(g_i - c^t s_i^m)y_i^k - \sum_{i\in\mathcal{I}\cup\mathcal{I}^O}\sum_{j\in\mathcal{I}\cup\mathcal{I}^D}\left(c^t d_{ij}\sum_{k\in\mathcal{K}} x_{ij}^k\right) \tag{1}$$

$$\text{subject to} \sum_{k\in\mathcal{K}} y_i^k \le 1,\ \forall\, i \in \mathcal{I}\cup\mathcal{I}^D \tag{2}$$

$$x_{ii}^k = 0,\ \forall\, i\in\mathcal{I},\ k\in\mathcal{K} \tag{3}$$

$$x_{ij}^k = 0,\ \forall\, i\in\mathcal{I}^O,\ j\in\mathcal{I}^D,\ k\in\mathcal{K} \tag{4}$$

$$\sum_{j\in\mathcal{I}} x_{ij}^k \le \tilde{y}_i^k,\ \forall\, i\in\mathcal{I}^O,\ k\in\mathcal{K} \tag{5}$$

$$\sum_{j\in\mathcal{I}} x_{ji}^k = y_i^k,\ \forall\, i\in\mathcal{I}^D,\ k\in\mathcal{K} \tag{6}$$

$$\sum_{\substack{j\in\mathcal{I}\cup\mathcal{I}^O\\ j\neq i}} x_{ji}^k = \sum_{\substack{j'\in\mathcal{I}\cup\mathcal{I}^D\\ j'\neq i}} x_{ij'}^k = y_i^k,\ \forall\, i\in\mathcal{I},\ k\in\mathcal{K} \tag{7}$$

$$x_{ij}^k(t_i + s_i^t + \tilde{t}_{ij}) \le t_j,\ \forall\, i\in\mathcal{I}\cup\mathcal{I}^O,\ j\in\mathcal{I},\ i\neq j,\ k\in\mathcal{K} \tag{8}$$

$$t_i = t_0,\ \forall\, i\in\mathcal{I}^O \tag{9}$$

$$t_0 \le t_i \le l_i,\ \forall\, i\in\mathcal{I} \tag{10}$$

[illegible] (11)

$$x_{ij}^k \in \{0,1\},\ \forall\, i\in\mathcal{I}\cup\mathcal{I}^O,\ j\in\mathcal{I}\cup\mathcal{I}^D,\ k\in\mathcal{K} \tag{12}$$

$$y_i^k \in \{0,1\},\ \forall\, i\in\mathcal{I}\cup\mathcal{I}^D,\ k\in\mathcal{K} \tag{13}$$

$$t_i \ge 0,\ \forall,\ i\in\mathcal{I}\cup\mathcal{I}^O \tag{14}$$

Takeaway: Considering social responsibility and humanity, together with operation optimizing, benefit companies greatly

Description

Vehicle Routing Problem

Simulated Annealing

Differential Evolution

Variable Neighborhood Search

Problem Scale

300 trucks X 12,000 orders

Over 10 billion decision variables

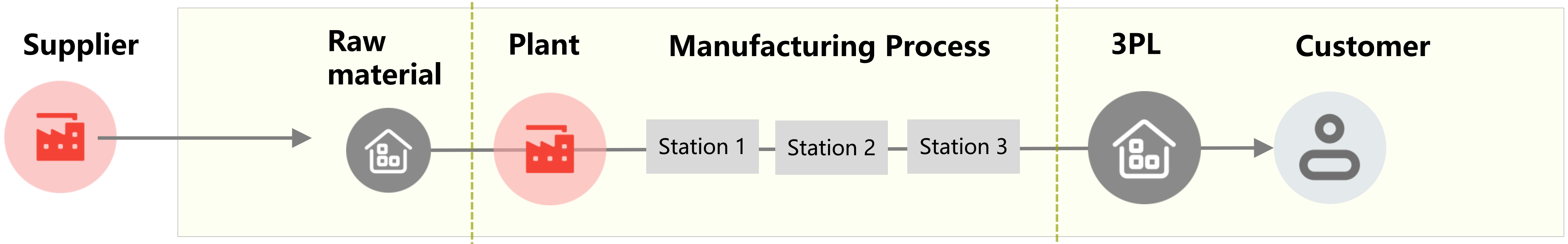
commercial solver **UNABLE To Solve**

customized algorithm **Solved in Minutes**

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.



01 Emission in Purchasing Process

02 Emission in Manufacturing Process

03 Emission in Supply Chain

Liuguo Chemical Industry S&OP-Background

- 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:

Problem	Change	Solution	Target
1 Excess capacity	S&OP	S&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	Improve S&OP skill Improve response speed to the market Improve the output-input ratio
2 Vast consignment	New marketing model		
3 Severe similarity	New system of products		
4 Control of energy	Sophisticated management	Build the KPI system of supply chain management	Improve sophisticated management skill

Liuguo-Shanshu S&OP Engine

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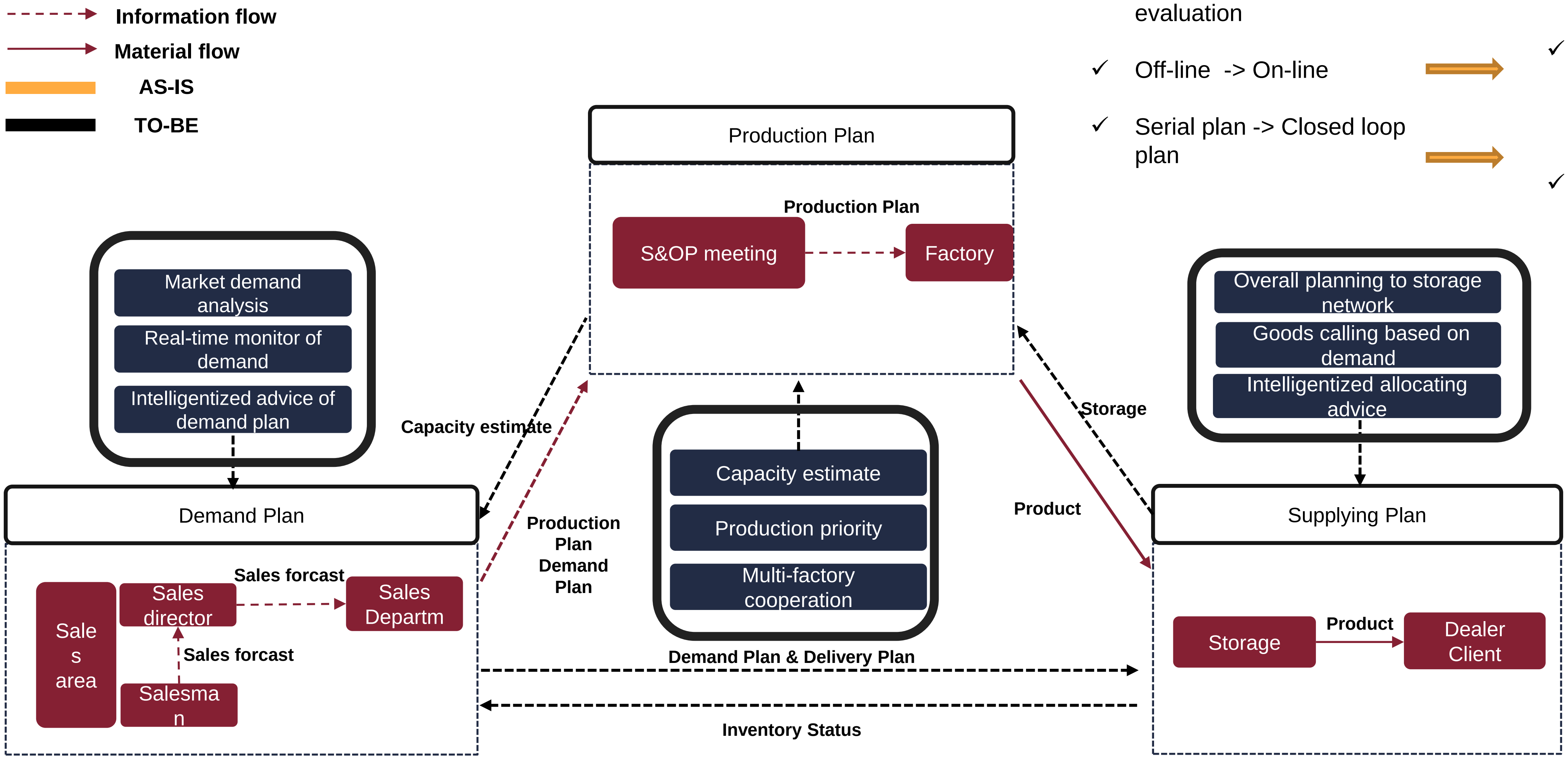
Shanshu S&OP engine strengthen LIUGUO Chemical Industry supply chain



Strengthen:

- ✓ Experience-> System evaluation
- ✓ Off-line -> On-line
- ✓ Serial plan -> Closed loop plan

- ✓ Save 5% transportation cost (allocating tansportation) .
- ✓ 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

$$\begin{aligned}
\textbf{Minimize}\quad & \textbf{production cost} \\
& + \textbf{inventory cost} \\
& + \textbf{transportation cost} \\
& + \textbf{carbon expenditure}
\end{aligned}$$

Minimize the total amount of carbon emission in the supply chain

Subject to:

$$\begin{aligned}
\text{(Delivery)}\quad & \delta_{i,t+1} = \delta_{i,t} + D_{i,t} - \sum_{p} d_{ipt} \\
\text{(Inventory)}\quad & n_{i,t+1} = n_{i,t} - d_{ipt} + x_{ipt} - \sum_{\mu_{ji}>0} \mu_{ji} x_{jpt} + \sum_{p'} y_{ip'pt} - \sum_{p'} y_{ipp't} \\
\text{(Capacity)}\quad & \sum_{i} \alpha_{ip} x_{ipt} \le C_p \\
\text{(Carbon control)}\quad & \text{carbon bound} \ge \sum_{i,p,t} \text{emission} \\
\text{(Operation rules)}\quad & \text{Many more ...}
\end{aligned}$$

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

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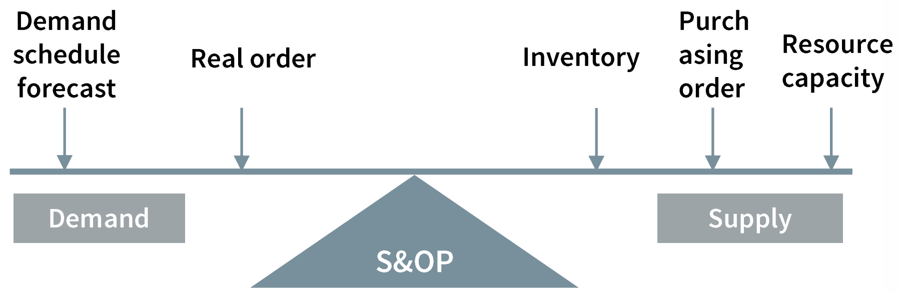
S&OP Definition



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 extern 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

Fluctuation and influence of the production, sales, inventory and supply plan, be cause of the change of multiple parameter

Cardinal Smart Planning Engine

Output

The production plan, sales plan and inventory plan guided on S&OP

- ✓ Sales qty, production qty, inventory plan and purchasing pan 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

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- Via operation optimization, arrange the production material resource more reasonable, realize profit maximum
- By sales forecast, understand market dynamics, planning reasonably the supply chain of company
- Using supply chain management method, profit-oriented, guiding integrally purchasing, production, inventory and forwarding
- Optimize capacity planning and manufacturing technique, further meet the environment compliance requirements

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

- 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

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

18Millions

Customer satisfaction rate improve

15%

Industry Chain

Carbon emission impact

Insure the gross profit rate

Improve the stability of supply chain

Thank You!