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PHYSICAL INTERNET CENTER
SUPPLY CHAIN & LOGISTICS INSTITUTE
SCHOOL OF INDUSTRIAL & SYSTEMS ENGINEERING
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CREATING THE NEXT®

I C I

More **COMPLEX** Current World

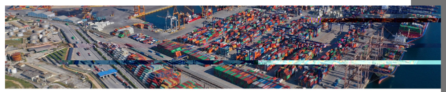
- Volatile
- Uncertain
- Complex
- Ambiguous

Greater **CHALLENGES** in Logistics and Supply Chain Management (LSCM)

- Flexible
- Visible
- Cooperative
- Hyperconnected

Physical Internet Paradigm

- A Metaphor of the Digital Internet
- To solve the inefficient and unsustainable situation in LSCM



I I D

PI

1. Smoothens the installation of necessary **IT system** for data sharing
2. Serves as a key trigger for **digitalizing** LSCM

F

D

1. Supports **seamless interconnection** of LSCM
2. Promotes the **dynamic decision-making**

I D

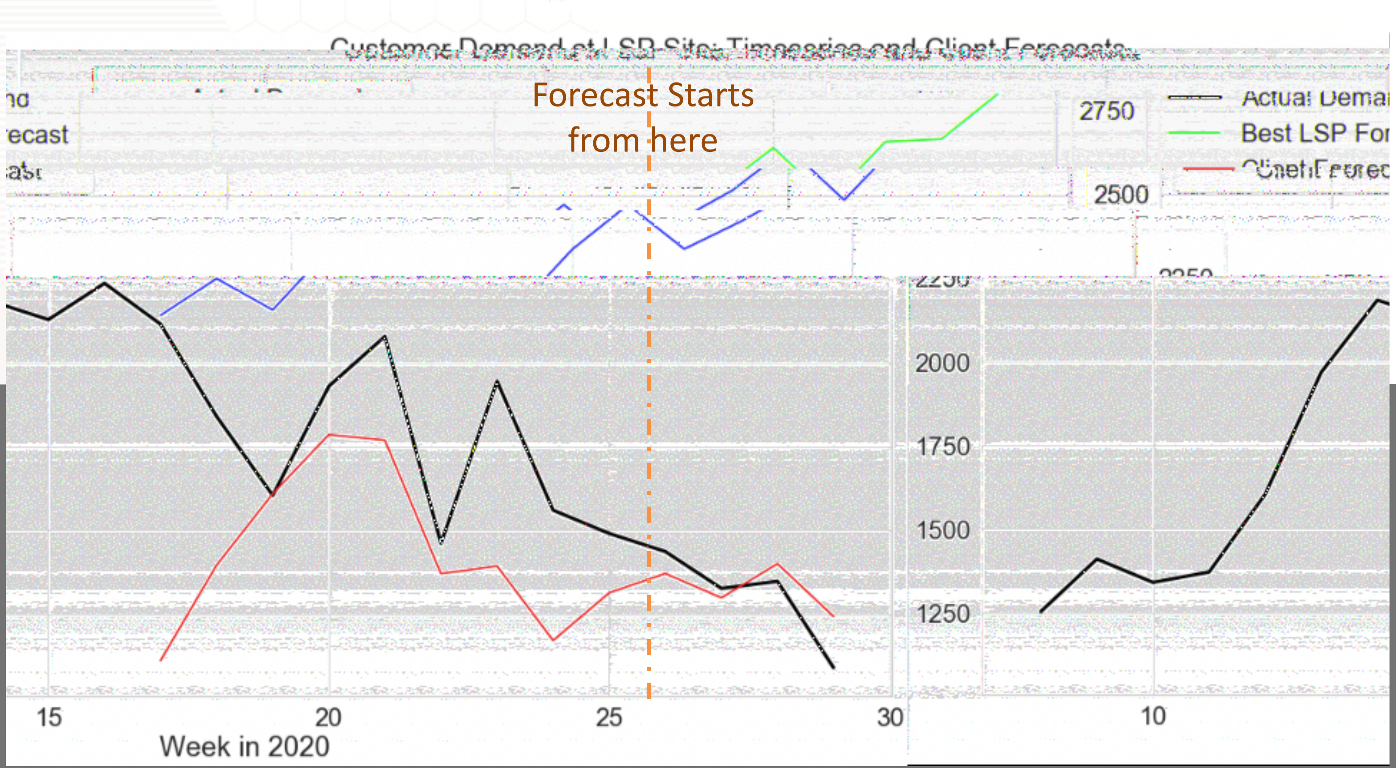


Figure 1: Comparing logistics service provider’s forecasts and client-provided forecasts with real client demand at logistics service provider site

L D

Data Integration

- Integration of databases
- Enterprise Application Integration (EAI)

Sharing Modified Data

- Modifying key contributions of raw data

Federated Learning

- Training global model instead of sharing data

Data Privacy Issue

What if only utilizing insensitive data or the data that clients are willing to provide?

H D E D

- Hyperconnected data ensemble requires as minimal data as possible

- The content of shared data is dependent on clients' choice
  - Aggregated data such as the overall activity forecast
  - ❌ detail information on product or SKU level
  - ❌ Key models
  - ❌ Production plan

H D E F L D

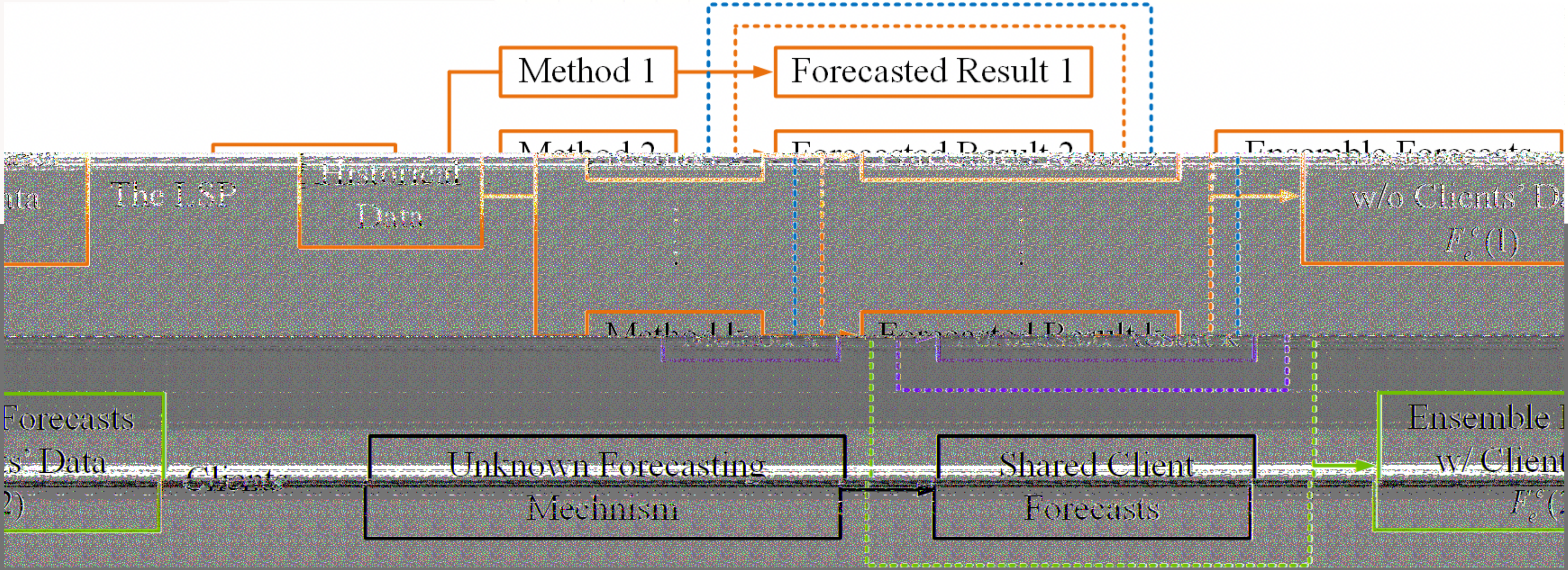
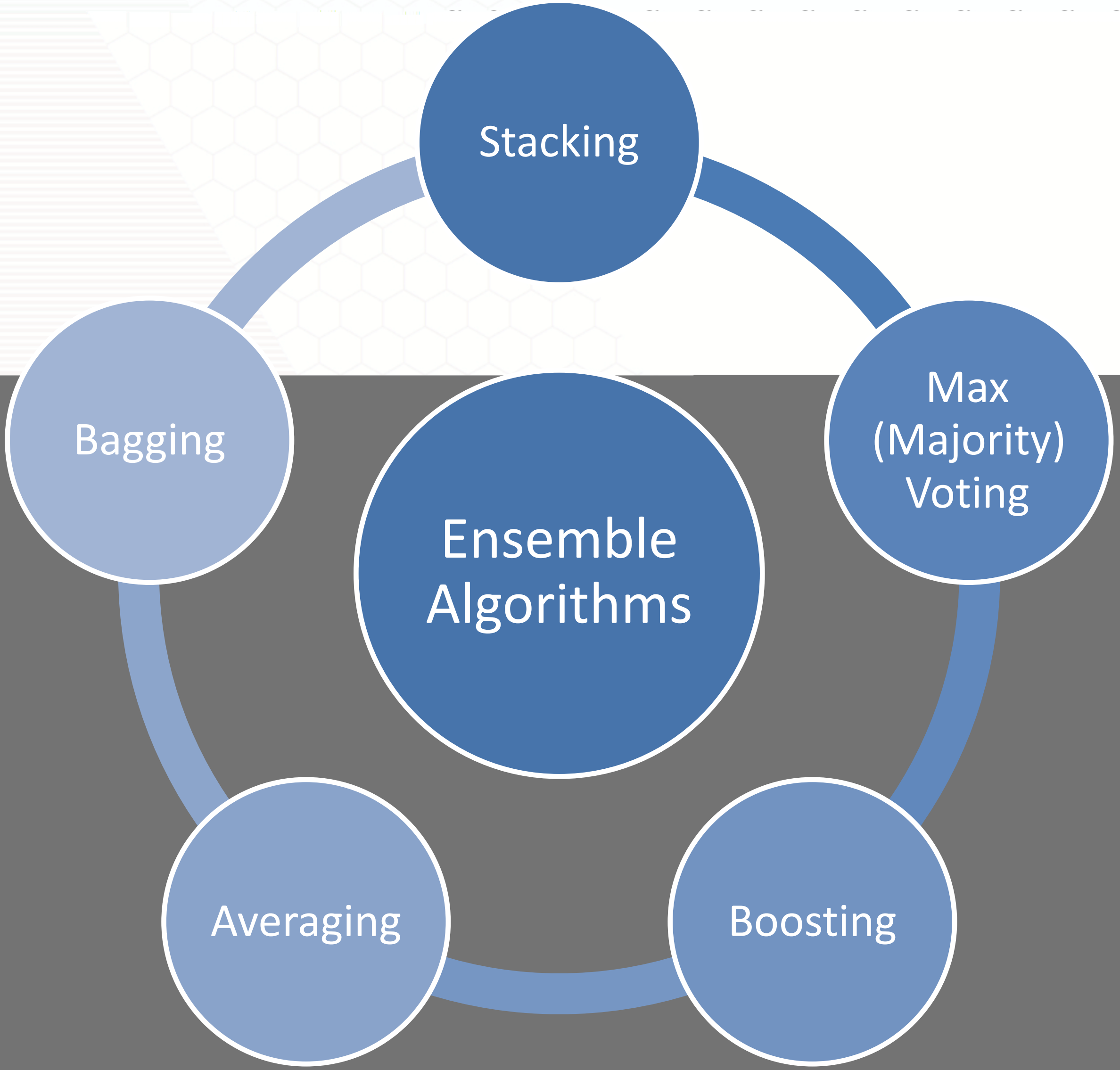


Figure 2: The Framework of logistics demand prediction with hyperconnected data ensembles

E A


Stacking
Max (Majority) Voting
Boosting
Averaging
Bagging
Ensemble Algorithms

Ensemble Method for including shared Client Forecasts

Under the general framework, we propose a weighted average ensemble method for including forecasts shared by client, with data-driven time series forecasts generated by the LSP:

$$F_e^c(1) = \sum_{j=1}^{k} F_{LSP_j}^c \alpha_j,\ \sum_{j=1}^{k} \alpha_j = 1,$$

$$F_e^c(2) = \sum_{j=1}^{k} F_{LSP_j}^c \alpha_j + F_c^c \alpha_{k+1},\ \sum_{j=1}^{k+1} \alpha_j = 1,$$

where,

- superscript c: the client level
- $F_e^c(1)$: the ensembled forecast without shared client data
- $F_e^c(2)$: the final forecast with client data ensembles
- $F_{LSP_j}^c$: the forecasted result generated by the j^{th} method from the LSP
- F_c^c: the forecast shared by clients
- α_j: the j^{th} weighting parameter and $0 \le \alpha_j \le 1$

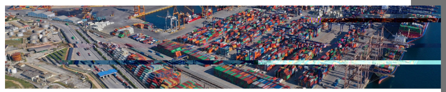
Experiments: Ensemble Methods for major Logistics Service Provider

A major LSP in North America has access to 2.5 years of historical daily demand data for the client's products at 2 sites, i.e. number of pallets shipped from the site to the destination.

The historical data is subject to seasonal fluctuations, and the LSP incorporates 4 timeseries forecasting methods at a daily level:

- Holt-Winters (HW) method (Winters, 1960) - $F_{LSP_1}^{C}$
- Double-Seasonal (DS) method (Taylor, 2003) - $F_{LSP_2}^{C}$
- Multi-Seasonality (MS) method (Gould et al., 2008) - $F_{LSP_3}^{C}$
- Bouchard-Montreuil (BM) method (Bouchard and Montreuil, 2009) - $F_{LSP_4}^{C}$

The client provides weekly aggregated demand forecast for a 13-week horizon for each site. With access to 50 such weekly forecasts (*50 Start Dates*), we conduct experiments to generate logistics demand forecast with data ensembles.



Experiments: Ensemble Methods for major Logistics Service Provider

We employ Monte-Carlo cross validation technique with a fixed number of iterations $N = 30$. For each iteration $i \in \{1, 2, \dots, N\}$, we randomly select 80% of dates as the training set from the total set of start-dates S ($|S| = 50$). Let the training set be $\hat{S} \in S$, and the test set $S' = S \backslash \hat{S}$, then the training error for i-th iteration is calculated using the following error metric:

$$E_i^{TR} = \frac{1}{|\hat{S}|} \sum_{s \in \hat{S}} MAE_s^i = \frac{1}{|\hat{S}|} \sum_{s \in \hat{S}} \frac{1}{13} \sum_{h=1}^{13} \left| A_{s,h}^i - F_{s,h}^i \right|,$$

$$E^{TR} = \frac{1}{N} \sum_{i=1}^{N} E_i^{TR}$$

where

- the superscript/subscript i refers to the number of the current iteration
- $\hat{S} \in S$ refers to the set of start-dates in the training set
- MAE_s^i refers to the Mean Absolute Error of the ensemble forecasts for a given start-date $s \in \hat{S}$
- $A_{s,h}^i$ represents the actual demand starting from date s for h period ahead
- $F_{s,h}^i$ represents the ensembled forecast made from s for h period ahead.

Finally, the optimal weighting parameters are selected by minimizing the final train error E^{TR}.

Results: Visualizing the impact of Ensemble Methods

Site 1: 8% decrease in test error E^{TE} upon integration with the client's forecasts

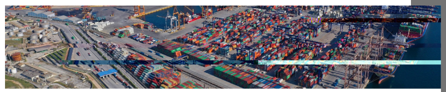
$$F_e^c(1) = 0.382 * F_{LSP_1}^c + 0.403 * F_{LSP_2}^c + 0.183 * F_{LSP_3}^c + 0.032 * F_{LSP_4}^c$$

$$F_e^c(2) = 0.252 * F_{LSP_1}^c + 0.297 * F_{LSP_2}^c + 0.067 * F_{LSP_3}^c + 0.056 * F_{LSP_4}^c + 0.328 * F_c^c$$

Site 2: 30% decrease in test error E^{TE} upon integration with the client's forecasts

$$F_e^c(1) = 0.020 * F_{LSP_1}^c + 0.977 * F_{LSP_2}^c + 0.0032 * F_{LSP_3}^c$$

$$F_e^c(2) = 0.0004 * F_{LSP_1}^c + 0.235 * F_{LSP_2}^c + 0.028 * F_{LSP_3}^c + 0.736 * F_c^c$$



Results: Including client forecasts significantly improves accuracy

Site 1

Demand Forecast Method	CV Error Train	CV Error Test	Improvement Train	Improvement Test
Best LSP Forecast DS	467.27	456.71		
Ensemble of LSP Forecasts $F_e^c(1)$	459.50	449.71	**1.66%**	**1.53%**
Client Forecast $F_{customer}^c$	503.81	482.28	**-7.82%**	**-5.60%**
Ensemble with Client Forecast $F_e^c(2)$	444.15	419.50	**4.95%**	**8.15%**

Site 2

Demand Forecast Method	CV Error Train	CV Error Test	Improvement Train	Improvement Test
Best LSP Forecast DS	450.09	485.31		
Ensemble of LSP Forecasts $F_e^c(1)$	450.67	485.75	**-0.13%**	**-0.09%**
Client Forecast $F_{customer}^c$	342.15	359.69	**23.98%**	**25.88%**
Ensemble with Client Forecast $F_e^c(2)$	324.42	338.09	**27.92%**	**30.34%**

Improvement I is measured as the decrease in CV error $E^{T:TR\ or\ TE}$ of method F versus the best LSP forecast F'

$$I = \frac{E_{F'}^{T} - E_{F}^{T}}{E_{F'}^{T}}$$

The ensemble of the LSP's data with the insensitive client's data improves overall forecasting accuracy

C

- Proposed a hyperconnected data ensembled framework based on data sharing under Physical Internet (PI) paradigm
  - Requires as minimal data as possible
  - The content of shared data is dependent on the clients’ choices in order to avoid the data privacy issue

- Conducted computational experiments
  - Demand prediction accuracy increases by integrating the aggregated forecasts from clients

Thanks!

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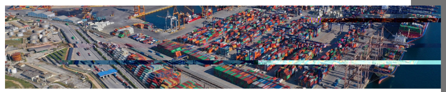

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