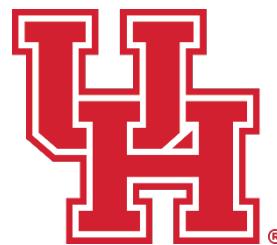
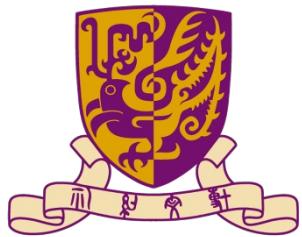


# FEDERATED SHIFT-INVARIANT DICTIONARY LEARNING ENABLED DISTRIBUTED USER PROFILING

**Qiushi Huang, Wengian Jiang, Jian Shi, Chenye Wu, Dan Wang and Zhu Han**



Q. Huang, W. Jiang, J. Shi, C. Wu, D. Wang and Z. Han, "Federated Shift-Invariant Dictionary Learning Enabled Distributed User Profiling," in IEEE Transactions on Power Systems, doi: 10.1109/TPWRS.2023.3296976.

# UNDERSTANDING USER BEHAVIOR IS A KEY ENABLER

- Active distribution network is crucial to the operation of a power grid with high penetration of renewable energies.
- And understanding user behaviors is **a key enabler** of active distribution network.

- How to understand user behaviors?
- What are the practical challenges?



Source: <https://www.varonis.com/blog/what-is-user-behavior-analytics>

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# CONVENTIONAL WISDOM

- The conventional wisdom is to conduct user profiling (i.e., clustering).
- Though effective, it faces several practical obstacles.
- Clustering requires massive data and **each single data holder may not have enough data to understand all kinds of users.**
- Also, data are the crucial assets for each data holder. Hence, **data holders may not want to directly exchange the data with each other.**



Source 

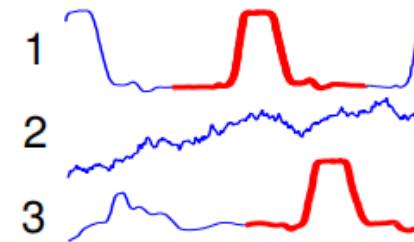
# OUR IDEA

- **Distributed User Profiling Based on Federated Learning & Dictionary Learning**
- Our idea is based on a simple observation:
  - Each user's data are the energy consumption aggregation of all its appliances.
  - Hence, the energy consumption patterns of those appliances can serve as the **dictionary**, which is used to construct the user's energy consumption data.
  - If the dictionary is rich, then the user profiling can be done more accurately.
- Hence, we propose that each data holder **first** conducts the dictionary learning based on its own data, and **then** exchange the dictionary with each other based on the **federated learning** framework.

# STEP 1: SHIFT-INVARIANT DICTIONARY LEARNING FOR USER PROFILING

Learn dictionary based on end users' load series  
Cluster the derived pattern matrices  $D$

Intuitive Idea



Time Warp

Making basis vector shift-invariant

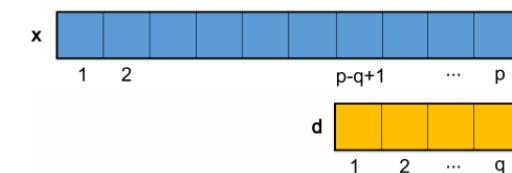
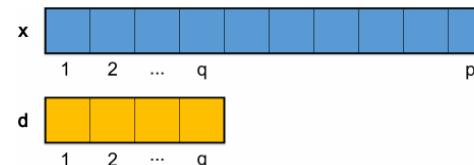


Shifting Operator

$$\Psi(d_k, [\beta]_k) = \begin{cases} [d_k]_{t - [\beta]_k}, & \text{if } 1 \leq t - [\beta]_k \leq q \\ 0, & \text{otherwise} \end{cases}$$

## Shift-Invariant Dictionary Learning

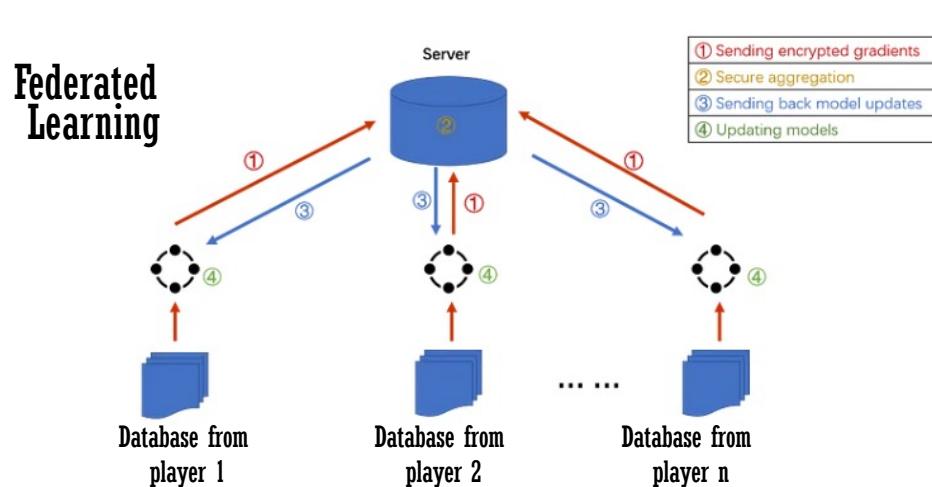
$$\min_{D, [\beta_j]_k} \sum_{j=1}^J \frac{1}{2} \left\| x_j - \sum_{k=1}^K [\alpha_j]_k \Psi(d_k, [\beta_j]_k) \right\|_2^2 + \lambda \sum_{j=1}^J \|\alpha_j\|_1$$



The same basis with different shifts

# STEP 2: FEDERATED SHIFT-INVARIANT DICTIONARY LEARNING CLUSTERING

- Incorporate federated learning
- Enable distributed user profiling without exchanging the datasets with each other



## Solution Procedure:

### 1. Local user dictionary learning

$$\min_{m^* \in [1, \dots, M], \alpha_j} \sum_{x_j \in P_u} \frac{1}{2} \left\| x_j - \sum_{k=1}^K [\alpha_j]_k \Psi(d_k^{m^*}, [\beta_j]_k) \right\|_2^2 + \lambda \|\alpha_j\|_1$$

### 2. Local dictionary updating

$$\min_{d_k^{m^*}} \sum_{x_j \in P_u} \frac{1}{2} \left\| x_j - \sum_{k=1}^K [\alpha_j]_k \Psi(d_k^{m^*}, [\beta_j]_k) \right\|_2^2$$

### 3. Dictionary aggregation (federated averaging)

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# NUMERICAL EVALUATION

**Dictionary learning helps**

■ Dictionary learning better reveals the load series patterns.

**Distributed implementation comes with a cost.**

■ The federated framework significantly improves the computation efficiency at the cost of slightly reduced v-measure, h-score and c-score.

TABLE I: Clustering Performance Comparison.

Evaluation	SIDL-clustering	$K$ -means	GMM	$K$ -shape	SC
h-score	0.9203	0.8714	0.7253	0.8942	0.8906
c-score	0.9453	0.9053	0.7451	0.9070	0.8934
$v$ -measure	0.9322	0.8876	0.7349	0.9004	0.8920

TABLE II: Performance Comparison between Centralized SIDL Clustering and Federated SIDL Clustering.

Method	$v$ -measure	h-score	c-score	Comp. Time
Central	0.9322	0.9203	0.9453	264min
Federated	0.9115	0.8972	0.9269	52min