IBM **Research**

Collaborative Anomaly Detection on Blockchain from Noisy Sensor Data

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Agenda

- Background: towards collaborative learning platform
- Problem setting
- Multi-task unsupervised learning for anomaly detection
- Updating global- and local state variables
- Concluding remarks

Development of Blockchain: From currency transfer to general business transaction

- Blockchain 1.0: Bitcoin
  - Specifically designed for currency transfer
  - Account identity is protected but transactional records are public
  - Verifying a transaction is trivial: just check the account balances
  - Futuristic consensus algorithm (“proof-of-work”) that lacks deterministic guarantees

- Blockchain 2.0: Smart-Contract-enabled transactional platform
  - Designed to be able to handle “general” business transactions
  - Public or semi-closed (membership, permissioned)
  - Verifying a transaction is not straightforward
  - Traditional consensus algorithm (e.g. PBFT) is typically used

Using Blockchain for IoT applications

- Two major data types
  - Traceability data: categorical, deterministic, may be incorrect but noise-free
    - ✓ Parts, inventories, work orders, SCM, CRM, etc.
    - ✓ Many attempts: food traceability (Walmart), shipping goods traceability (Maersk), etc.
  - focus → Sensor data: real-valued, stochastic noise
    - ✓ Raw sensor signals such as temperature, pressure
- Expectations towards novel business applications
  - Decentralized SCM
  - Utility-based pricing of resources (sensors, algorithms, etc.)
  - etc.

Redefining Blockchain as collaborative learning platform

- Most of the existing Blockchain-based IoT applications are sort of static data storage. We want to go one step further

- “Blockchain 3.0”: Platform for ***collaborative learning***
  - A platform to create new business insights through knowledge sharing among multiple parties in a Blockchain-specific way

- Key question: how can we create a new business value through data exchange on Blockchain?

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Sharing sensor data on Blockchain: Challenges

- Challenges to put sensor data onto Blockchain networks
  - Validation
  - Consensus

- Validation

focus

  - What if a new observation shared is incorrect?
    - ✓ This is a general issue for most of smart contracts
  - Need automatic down-weighting mechanism for less informative observations

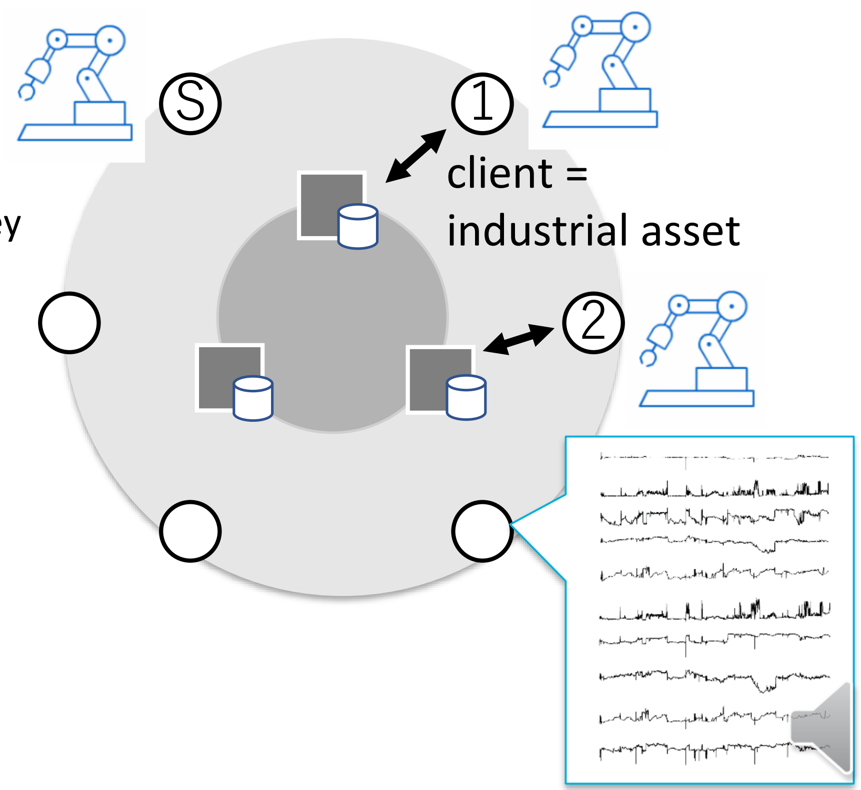
- Consensus
  - Most of the existing Blockchain system do NOT assume noisy sensor signals
    - ✓ (out of the scope of this work)

Collaborative condition-based monitoring of industrial assets: Problem setting

- System: distributed competing industrial assets
  - Mining tools, manufacturing tools, etc.
  - They want to keep their data privately, but they want to exploits other data

- Data: real-valued multi-variate noisy sensor signals
  - e.g. temperature, pressure, ...

- Goal: Collaboratively build an anomaly detection model through Blockchain transactions

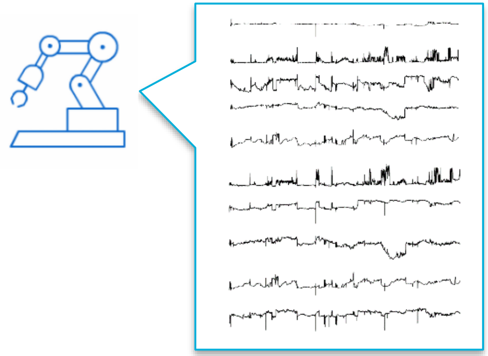


Collaborative condition-based monitoring of industrial assets: Requirements

- Capable of handling noisy data

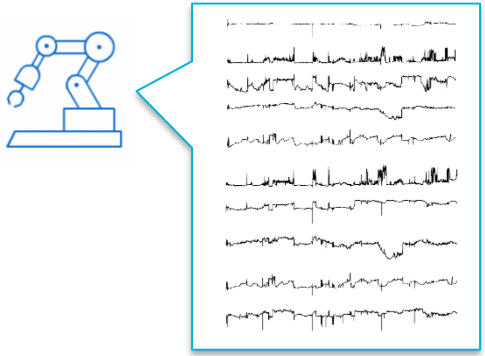
- Capable of taking an optimal balance between individuality vs. commonality of the assets

- Capable of preserving data privacy
  - Assumption of competing assets: Do not want to share their own data but want to exploit other one's data
  - Happens when assets belong to different companies



Collaborative condition-based monitoring of industrial assets: Approach overview

- Capable of handling noisy data
  - Probabilistic sample weighting scheme
- Capable of taking an optimal balance between individuality vs. commonality of the assets
  - Multi-task learning for anomaly detection
- Capable of preserving data privacy
  - Separation of global- and local state variables



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Doing multi-task learning (MTL) as Smart Contract

- Definition of multi-task learning:
  - A machine learning algorithm is said to be multi-task learning if the model consists a local part and a global part:

    (prediction model) = (global/shared part) + (local/individual part)

- A Smart Contract is characterized by a pair of (state variable, algorithm)

- We map an MTL-based anomaly detection model [Ide+ ICDM 17] onto a Smart Contract by properly defining state variables

Learn probability density under normal condition.
Define anomaly score as deviation from the normal state

Data

Prob. density

Anomaly score

Client 1
(in Singapore)

$\{\boldsymbol{x}^{1(n)} \in \mathbb{R}^M\}$

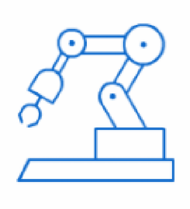
$p^1(\boldsymbol{x}^1 \mid \mathcal{D})$

all data

$-\ln p^1(\boldsymbol{x}^1 \mid \mathcal{D})$

⋮

Client *s*



$\{\boldsymbol{x}^{s(n)} \in \mathbb{R}^M\}$

multi-task learning (MTL)

$$p^s(\boldsymbol{x}^s \mid \mathcal{D})$$

$$= \sum_{k=1}^{K} \pi_k^s \, \mathcal{N}(\boldsymbol{x}^s \mid \boldsymbol{\mu}^k, (\Lambda^k)^{-1})$$

$-\ln p^s(\boldsymbol{x}^s \mid \mathcal{D})$

⋮

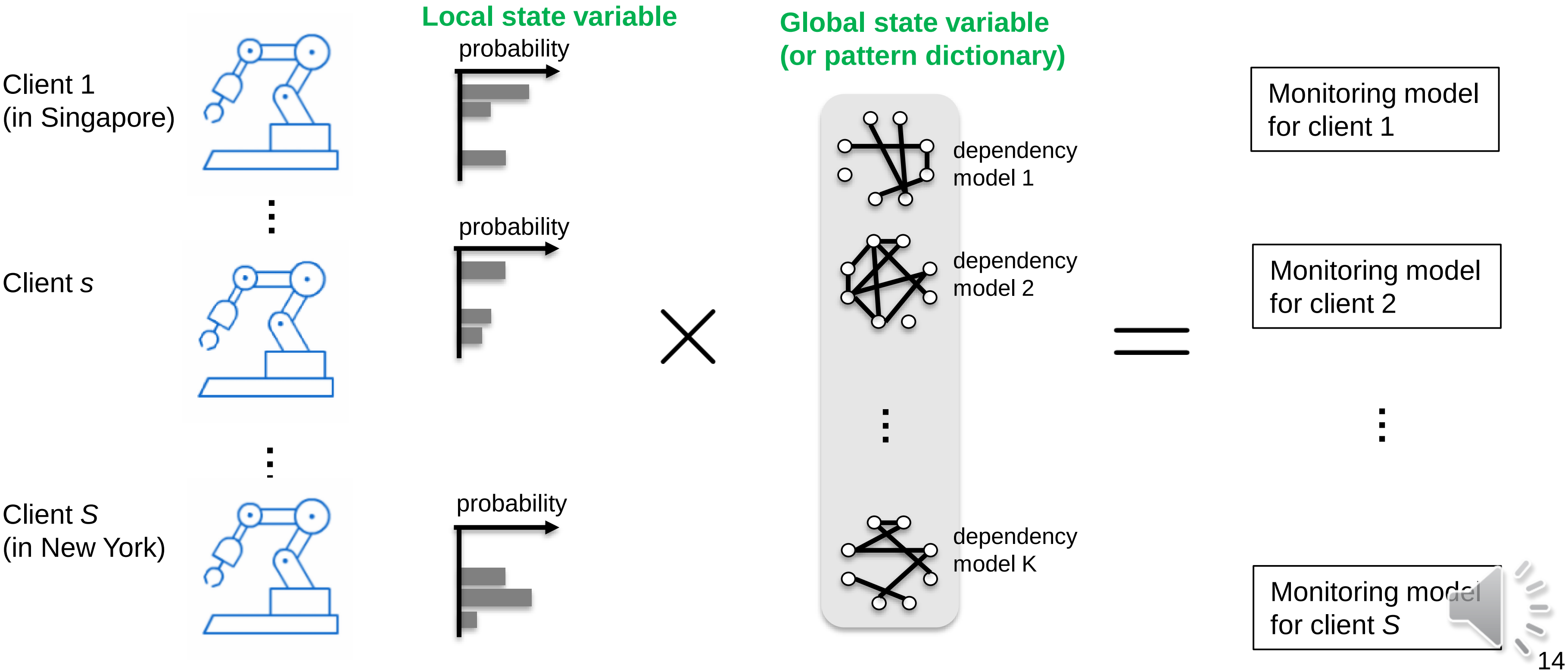
Client *S*
(in New York)

$\{\boldsymbol{x}^{S(n)} \in \mathbb{R}^M\}$

$p^S(\boldsymbol{x}^S \mid \mathcal{D})$

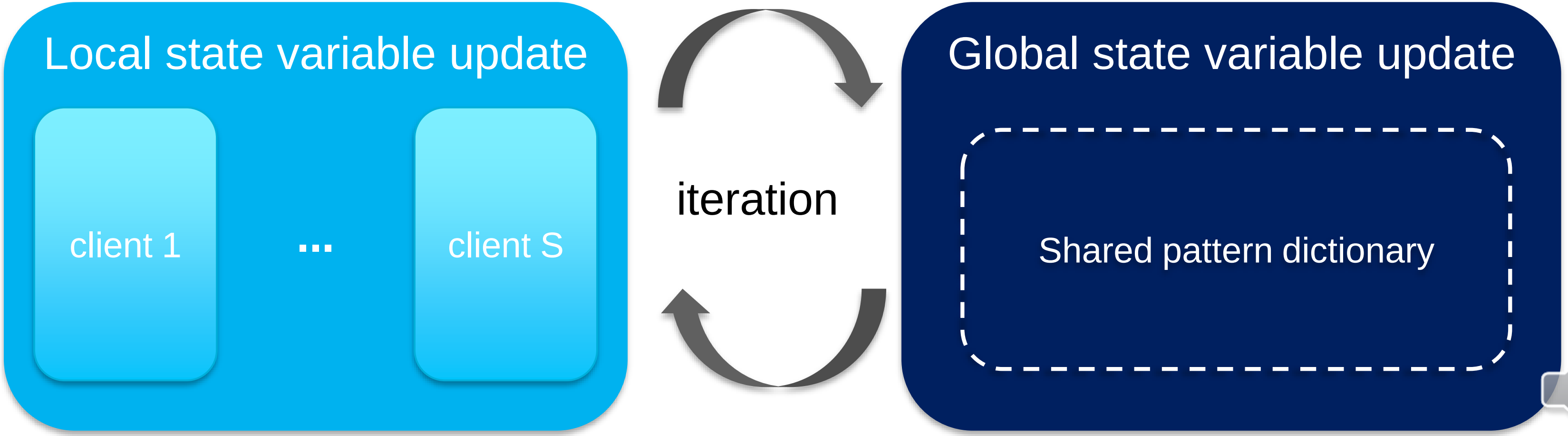
$-\ln p^S(\boldsymbol{x}^S \mid \mathcal{D})$

Each model is represented as a linear combination of shared dependency models



Learning model parameters from data

- Employ an EM algorithm for model inference
  - See the text for the detail
- The resulting algorithm is **iterative**:



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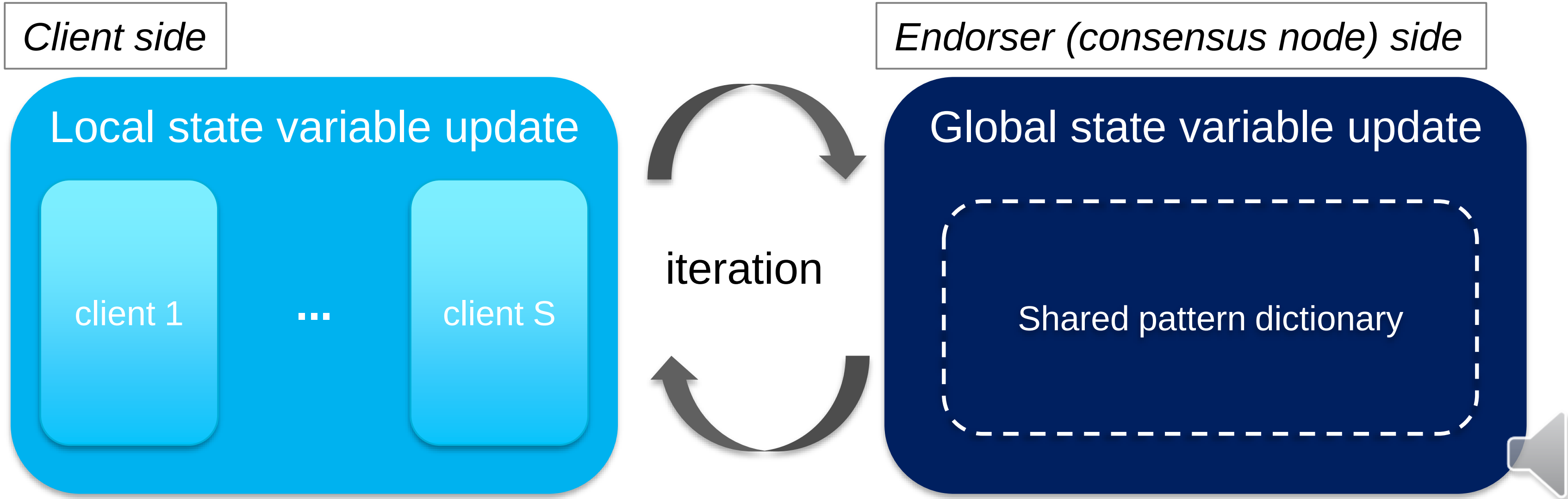
Local and global state variables are iteratively updated as Smart Contract

- Anomaly score function is written in terms of global and local state variables

$$a^s(\boldsymbol{x}^s \mid \boldsymbol{\theta}_{\mathrm{gl.}}, \boldsymbol{\theta}_{\mathrm{lo.}}) = -\ln p(\boldsymbol{x}^s \mid \boldsymbol{\theta}_{\mathrm{gl.}}, \boldsymbol{\theta}_{\mathrm{lo.}}),$$



The derived EM algorithm is naturally mapped into the local-global update framework

- Anomaly score function is written in terms of global and local state variables

$$a^s(\boldsymbol{x}^s \mid \boldsymbol{\theta}_{\mathrm{gl.}}, \boldsymbol{\theta}_{\mathrm{lo.}}) = -\ln p(\boldsymbol{x}^s \mid \boldsymbol{\theta}_{\mathrm{gl.}}, \boldsymbol{\theta}_{\mathrm{lo.}}),$$

Client side

$\boldsymbol{\theta}^s_{\mathrm{lo.}}$

Aggregated quantities

$$N_k^s \leftarrow \sum_{n=1}^{N^s} r_k^{s(n)},$$

$$\boldsymbol{m}_k^s \leftarrow \sum_{n=1}^{N^s} r_k^{s(n)} \boxed{\boldsymbol{x}^{s(n)}},$$

raw sample

$$\mathsf{C}_k^s \leftarrow \sum_{n=1}^{N^s} r_k^{s(n)} \boxed{\boldsymbol{x}^{s(n)} \boldsymbol{x}^{s(n)}}^\top,$$

$$\pi_k^s \leftarrow \frac{N_k^s}{\sum_{l=1}^{K} N_l^s},$$

iteration

Endorser (consensus node) side

$$N_k \leftarrow \sum_{s=1}^{S} N_k^s,$$

$$\boldsymbol{\mu}_k \leftarrow \frac{1}{\lambda_0 + N_k} \sum_{s=1}^{S} \boldsymbol{m}_k^s,$$

$$\Sigma_k \leftarrow \frac{1}{N_k} \sum_{s=1}^{S} \mathsf{C}_k^s + \boldsymbol{\mu}_k \boldsymbol{\mu}_k^\top,$$

$\boldsymbol{\theta}_{\mathrm{gl.}}$

How this algorithm meets the practical requirements

- Validating transactions for real-valued noisy data
  - EM algorithm automatically down-weights less informative observations
  - This can be viewed as automated validation of transactions
- Balancing between individuality vs. commonality
  - This is the very core concept of multi-task learning
- Preserving data privacy
  - Raw data is never shared beyond each client
  - Only aggregated statistics are shared with endorsers (consensus nodes)

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Conclusion

- We redefined Blockchain network as collaborative learning platform
- We showed that multi-task learning nicely fits the notion of Smart Contract by separating global and local state variables
- As a concrete IoT example, we wrote down an MTL-based dictionary learning algorithm for collaborative condition-based maintenance of industrial assets

Limitations of the current model and our on-going work

- Lack of an explicit consensus building mechanism
  - Traditional Byzantine Fault Tolerance mechanisms are not appropriate to IoT data
    - ✓ They implicitly assume categorical and deterministic data
  - Our recent approach has solved this issue
- Lack of theoretical guarantees on privacy preservation
  - We recently developed an improved version that has a mathematical privacy guarantee
- Lack of a realistic business model that motivates companies to participate in this network
  - On-going work is looking at an approach to incentivizing or penalizing clients based on the immutable Blockchain data, depending on contribution to dictionary learning

Thank you!