Machine Learning Models to Enhance the Science of Cognitive Autonomy

Ganapathy Mani, Bharat Bhargava, Pelin Angin, Miguel Villarreal-Vasquez, Denis Ulybyshev, Jason Kobes*

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Intelligent Autonomous Systems

- Autonomous Systems should be
  - Able to perform complex tasks without or with limited ongoing connection to humans.
  - Cognitive enough to act without a human's judgment lapses or execution inadequacies.

- Intelligent Autonomous Systems (IAS) are characterized as highly **Cognitive**, effective in **Knowledge Discovery**, **Reflexive**, and **Trusted**.

- The focus of this research will be on the smart cyber systems.

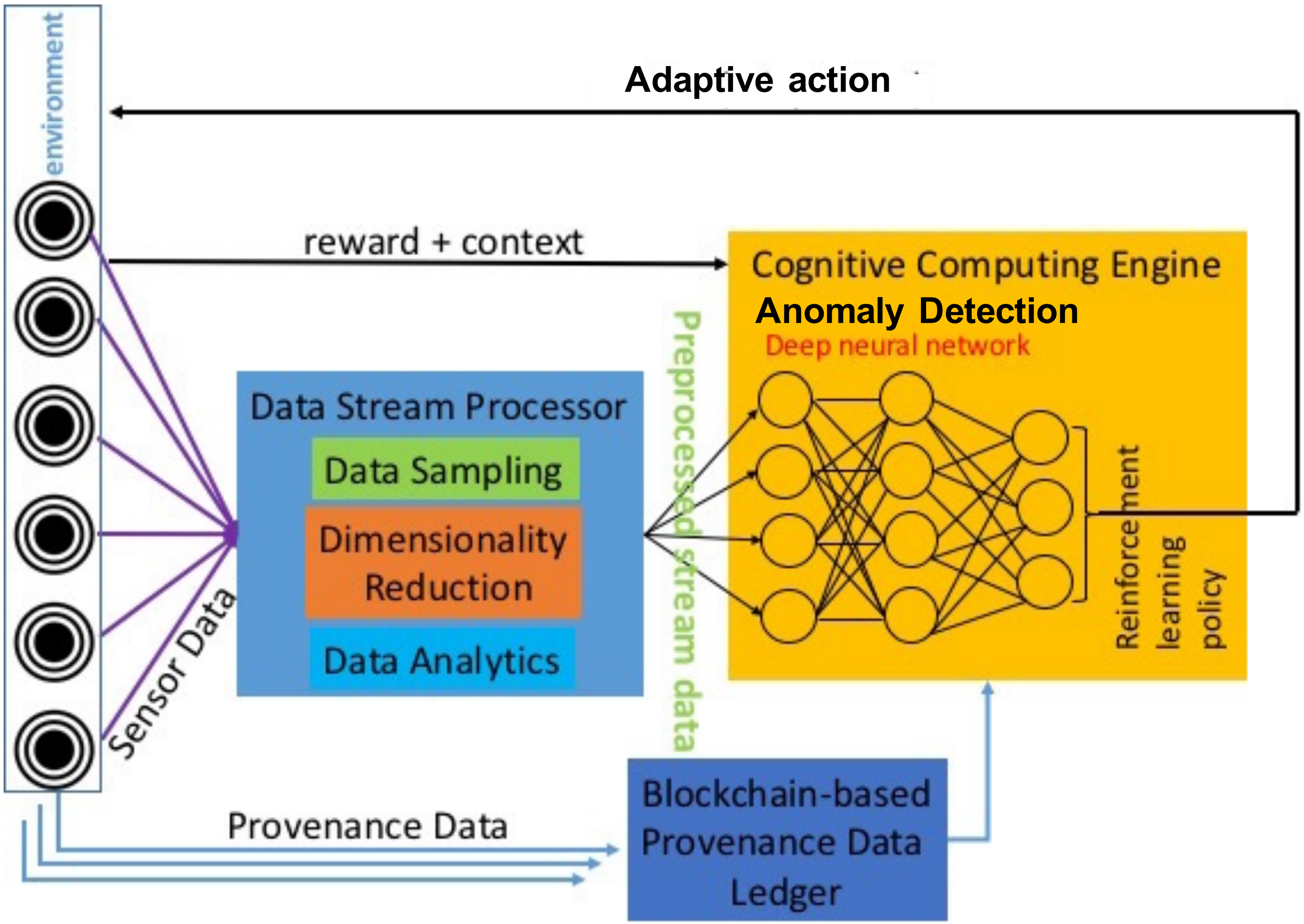
Motivation – A Holistic Approach

- Autonomous systems should learn at the network level as well as about their environment and context.

- Autonomous systems should be trained to work with
  - Meta-data, limited data, incomplete data, and unknown (new) data
  - Dynamic, unpredictable, and adversarial environment

- In this presentation, we will present theoretical framework and our implementation details.

Comprehensive IAS Architecture



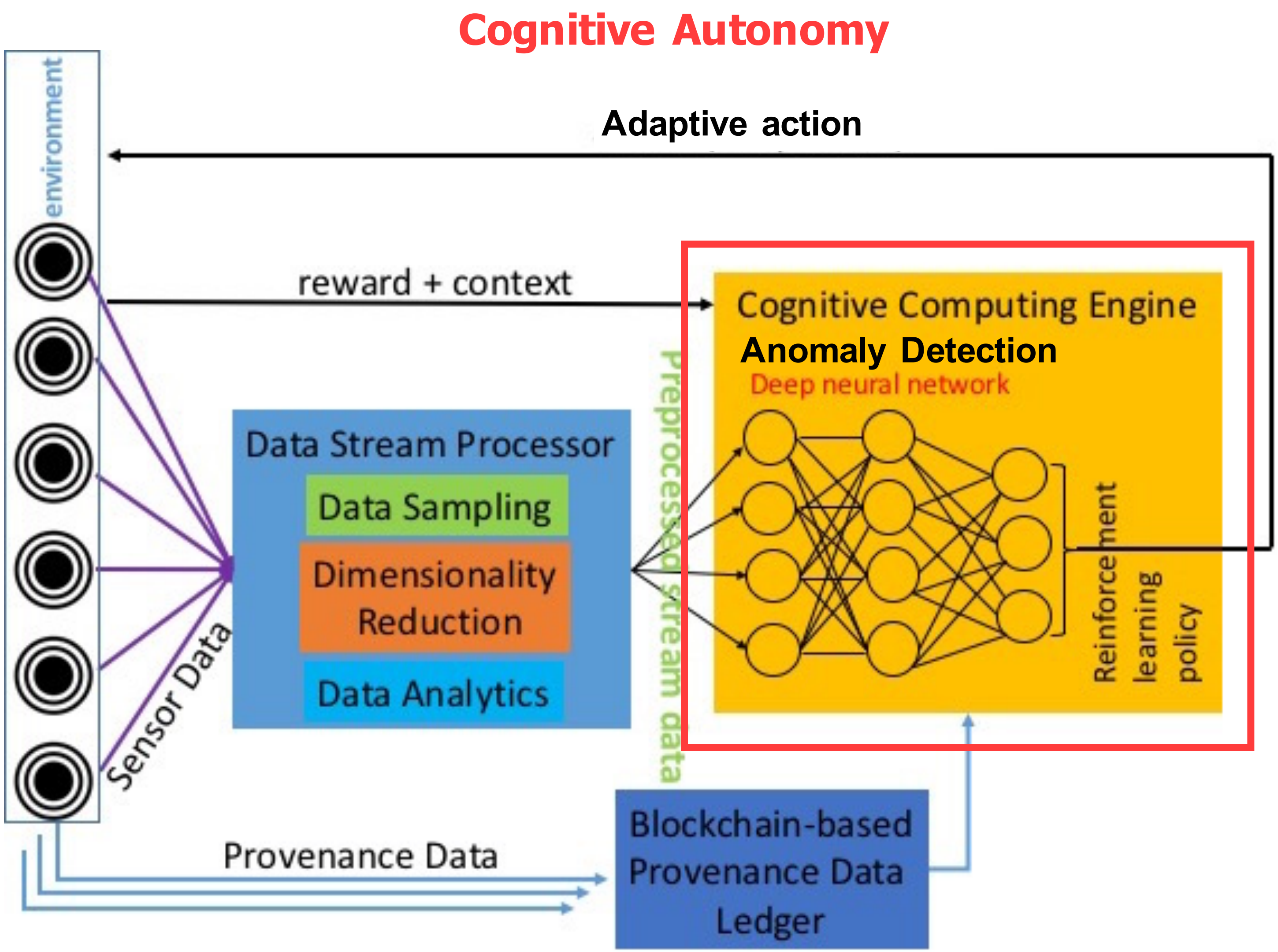
Implementation of Components of IAS

- **Cognitive Autonomy** & **Knowledge Discovery:**
  - Monitors and records system's activities (Data provenance and sequence of system calls)
  - Conducts privacy-preserving aggregated analytics on provenance data.
  - Utilizes Deep learning based anomaly detection by analyzing sequence of system calls.
- **Reflexivity:**
  - Adaptive actions are performed through graceful degradations without disrupting the ongoing critical processes by incremental learning.
- **Trust:**
  - Uses blockchain to store provenance data for trust.

Cognitive Autonomy

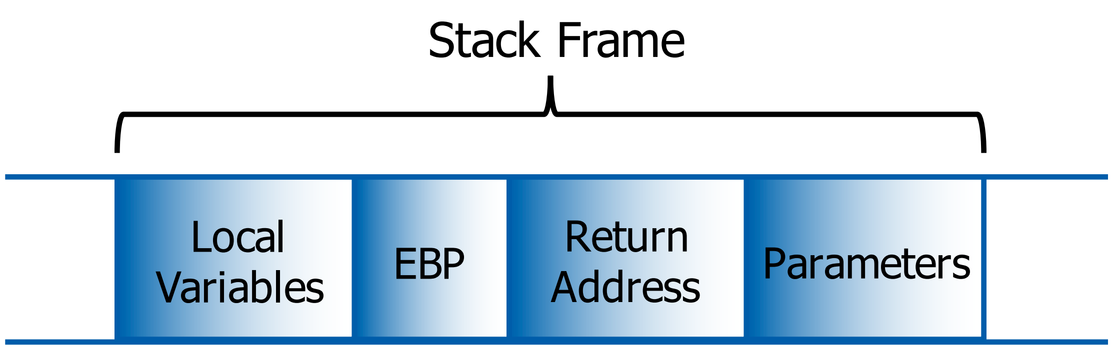
A Deep Learning Based Anomaly Detection Solution

Comprehensive Architecture of IAS



Problem Statement

- Programs store Return Addresses (control flow) along with data in the stack.
- Control-hijacking attacks execute arbitrary code on the target IAS program by hijacking its control flow.
- A Deep Learning based anomaly detection technique has been developed to protect IAS programs against these attacks.



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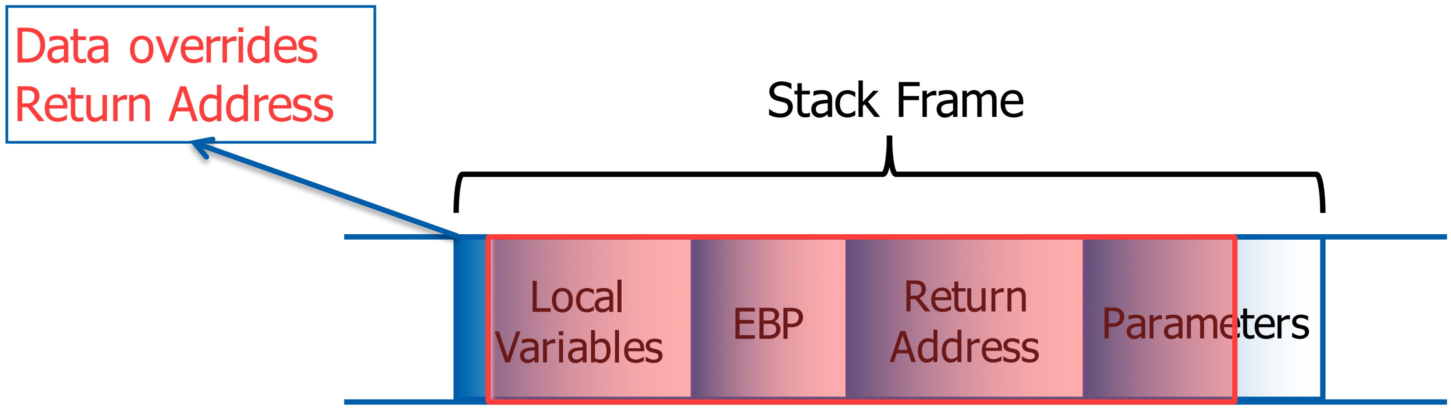

Research Approach

- An event e_i *is* defined as a function call (**system or library call**) in the execution trace of a program.
- Use Deep Learning to answer **the binary classification problem** of given a sequence of function calls (or system events) $e_1 e_2 e_3 \ldots e_k$ **whether or not the sequence should occur**?

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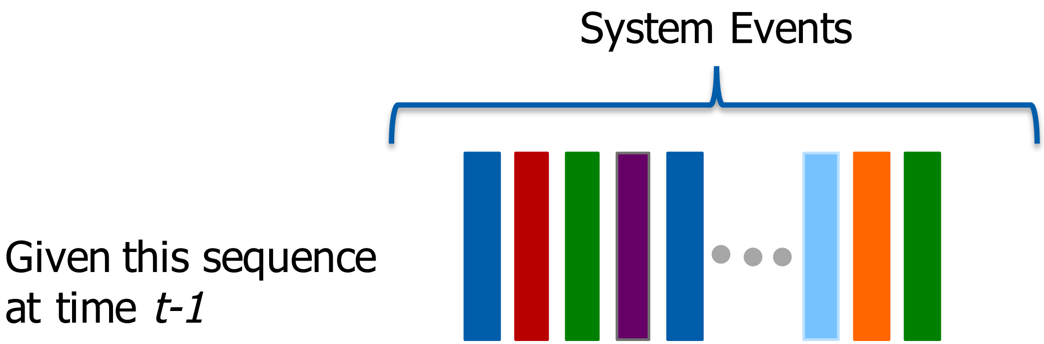

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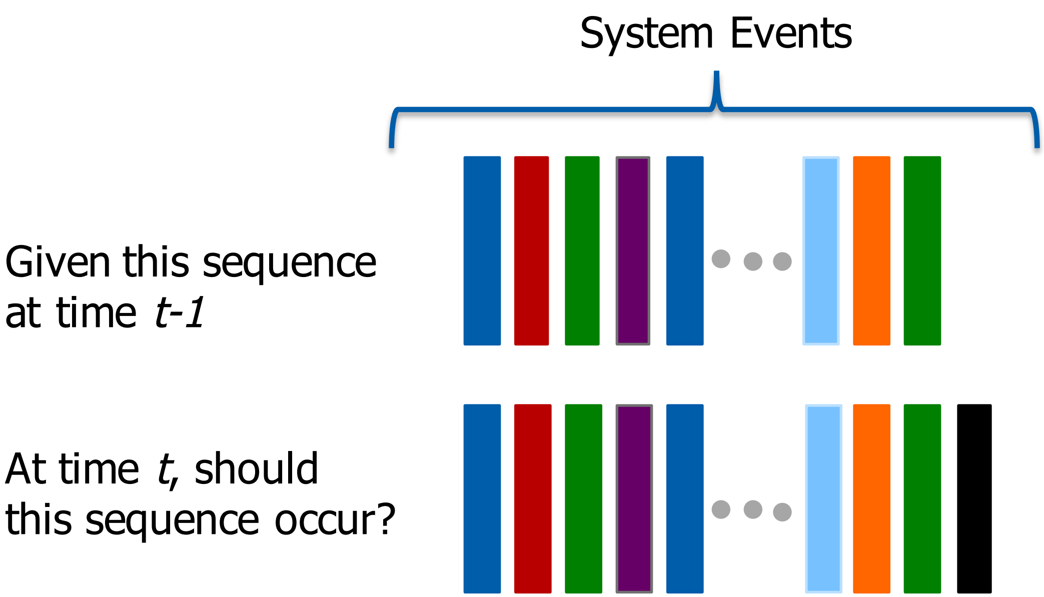


Types of attacks and mitigation

Attacks:

- **Code injection:** Malicious instruction sequences are executed using injected codes in the data portion of the stack. Examples: Buffer overflow and buffer specified injection.
- **Code reuse:** Malicious instruction sequences are executed without injecting external code. Examples: Return-oriented programming and memory disclosure.

Mitigation:

- Control Flow Integrity (CFI) is required.
- Deep Learning is used to guarantee Control Flow Integrity (CFI) as the model detects non-conforming sequences of execution traces in run time.

Deep Learning Based Anomaly Detection

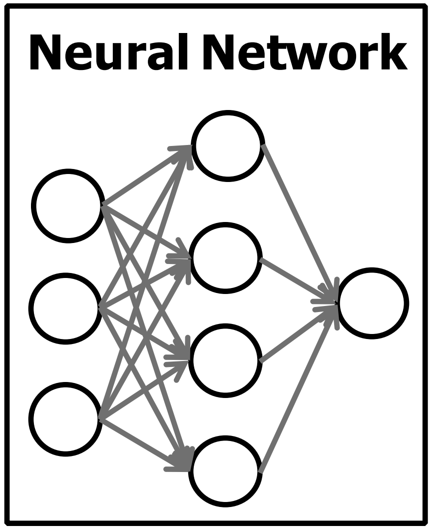
- For a given program, a code coverage is conducted to obtain all the possible execution traces.
- An event e_i *is defined* defined as a function call (**system or library call**) in the execution trace of a program.
- Each possible system event (function calls) is uniquely identified as they will form the vocabulary of system events.
- The Deep Learning model (neural network) is trained with the obtained sequences of events.
- The model is based on Recurrent Neural Networks: Long-Short Term Memory (**LSTM**) and Gated Recurrent Units (**GRU**.)

Deep Learning Based Anomaly Detection

- After training, given a sequence of events as input, the neural network produces as output an array of probabilities, one for each of the possible events in the system.
- At any time *t* each possible event (system call or library call) in the system is assigned a probability estimated with respect to the sequences of events **observed until** time *t-1*.
- At classification time *t*, the decision is made with respect to a pre-defined threshold of the top-*k* most likely events.

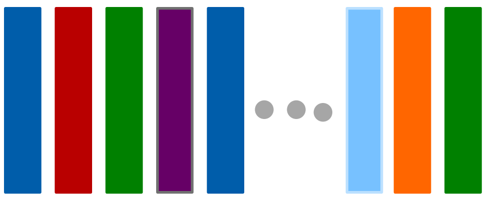
Deep Learning Based Anomaly Detection

Set of all system events



Deep Learning Based Anomaly Detection

Sequence of system events
at time *t-1*



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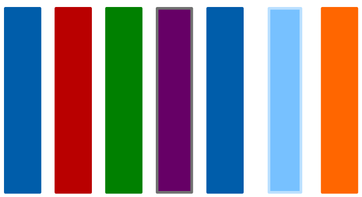
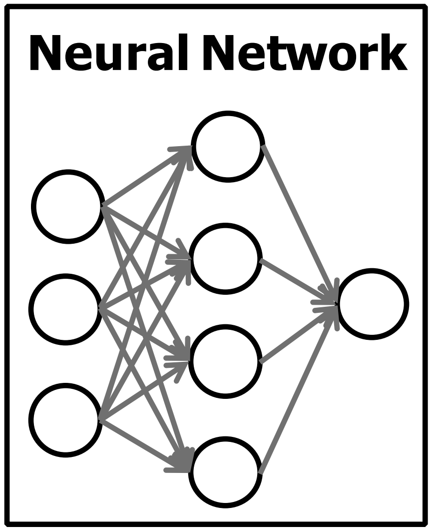
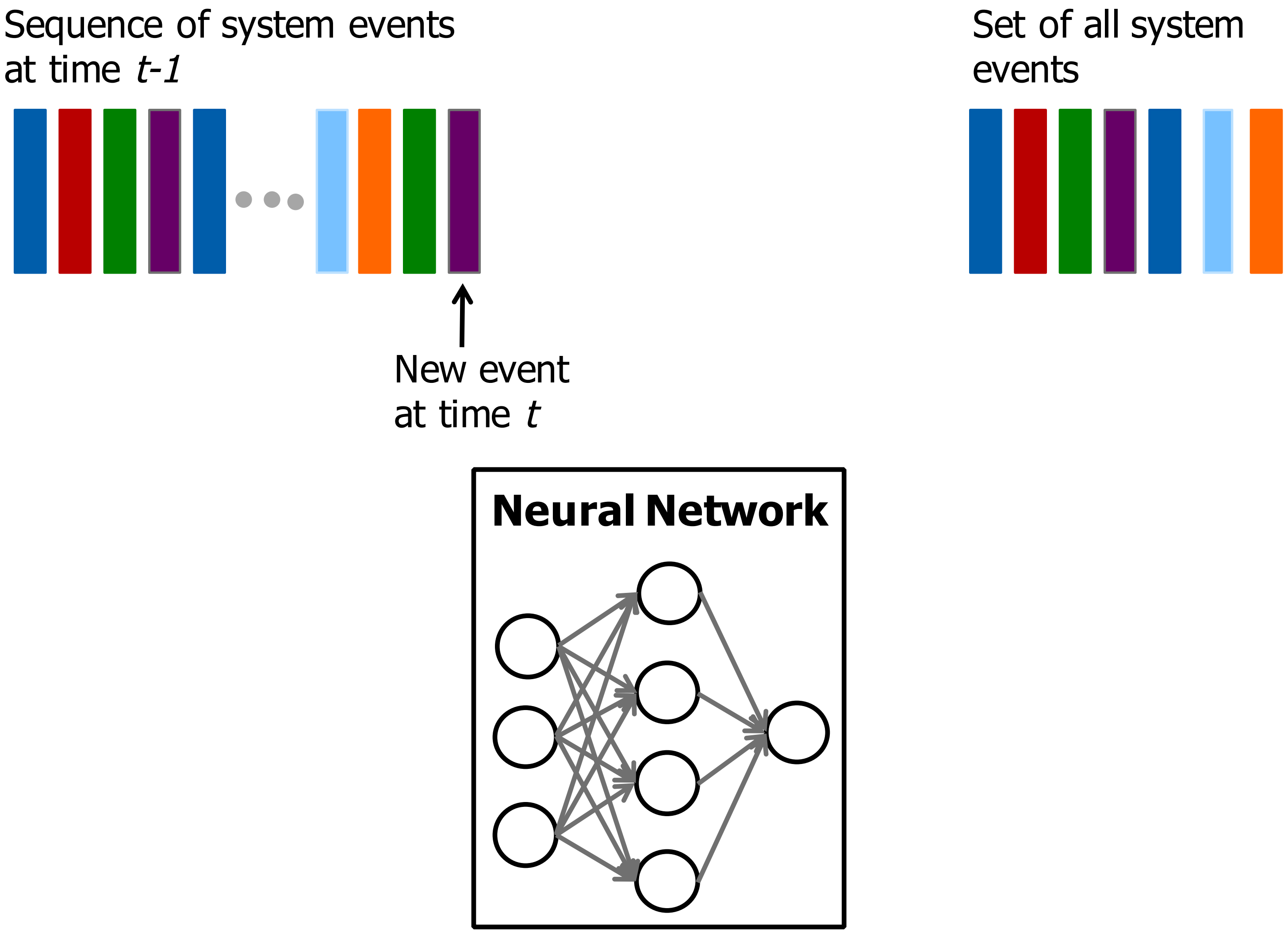




Deep Learning Based Anomaly Detection



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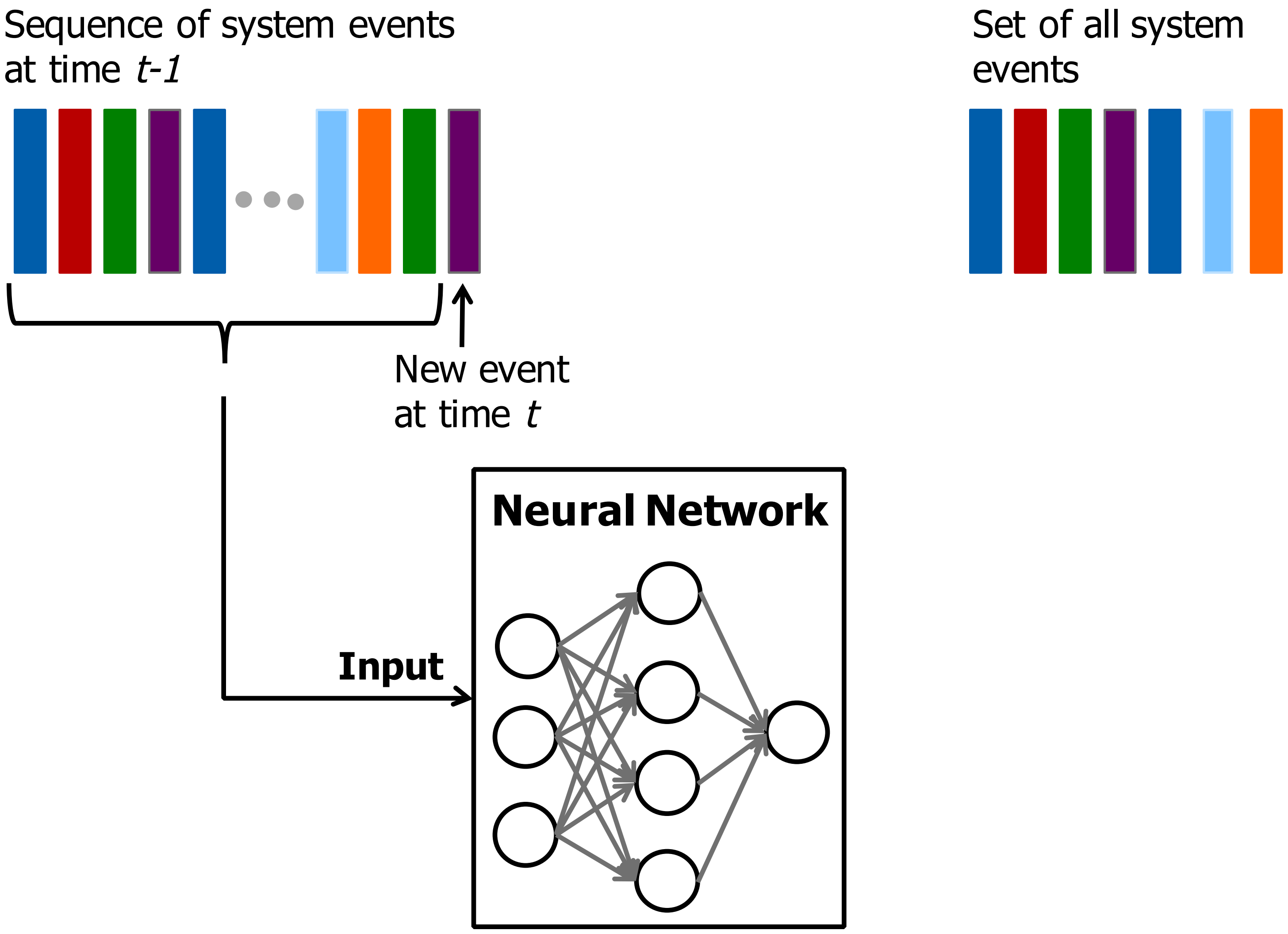

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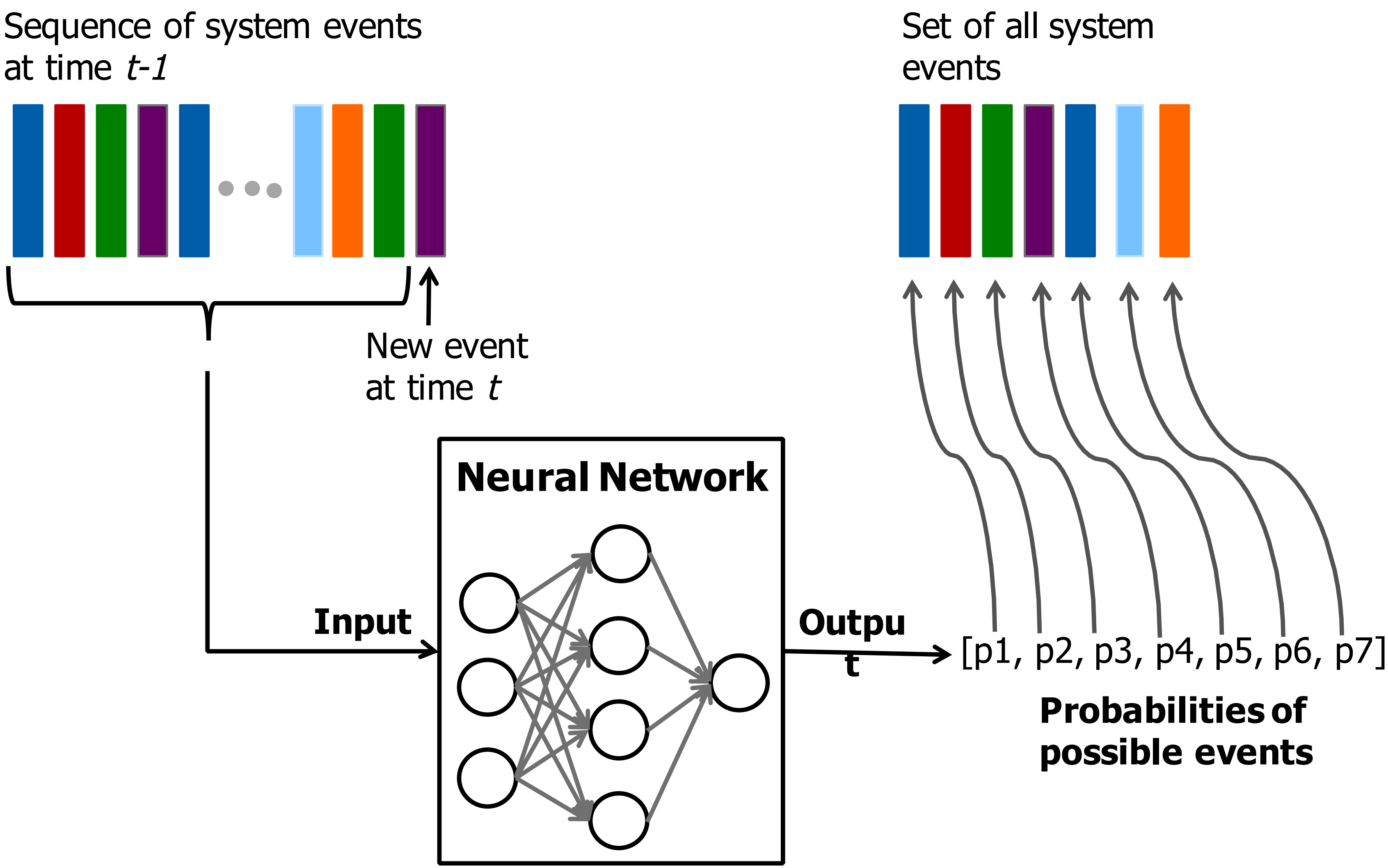

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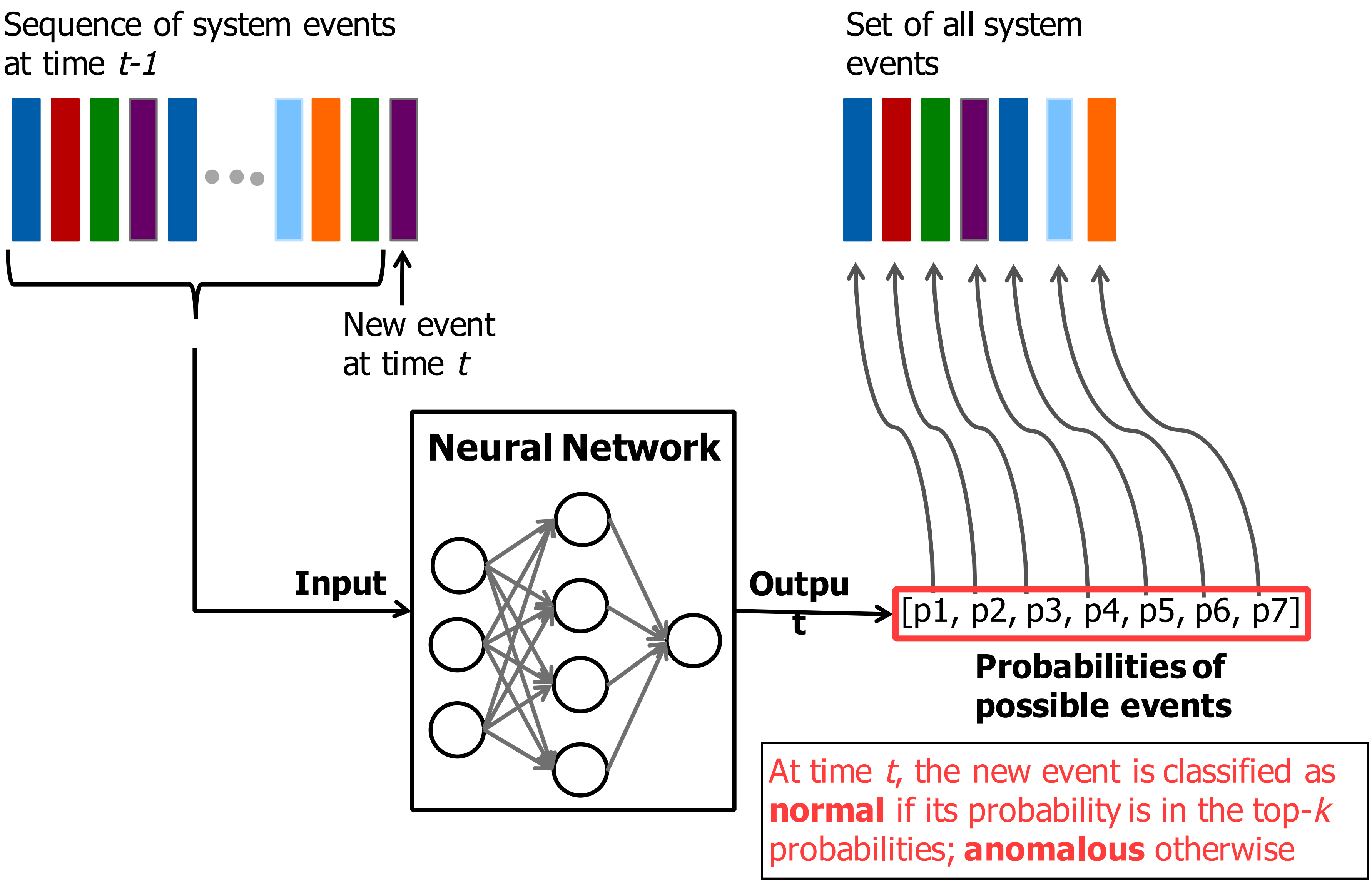


Deep Learning Based Anomaly Detection

Input: Sequence of events in the system
Output: normal or anomalous

- **Step 1:** Define a finite set E of events $e_1, e_2, ..., e_N$ in the system. Events occur in a time-series fashion.
- **Step 2:** At time $t-1$, given an observed series of events $\{e_i{}^1, e_i{}^2, ..., e_i{}^{t-1}\}$ (with $i = 1, 2, ...orN$) find the set K of the top k events to occur in time t.
- **Step 3:** At time t, the sequence $\{e_i{}^1, e_i{}^2, ..., e_i{}^{t-1}, e_i{}^t\}$ is non-anomalous if $e_i{}^t \in K$, otherwise anomalous.

Algorithm 1: Anomaly detection algorithm

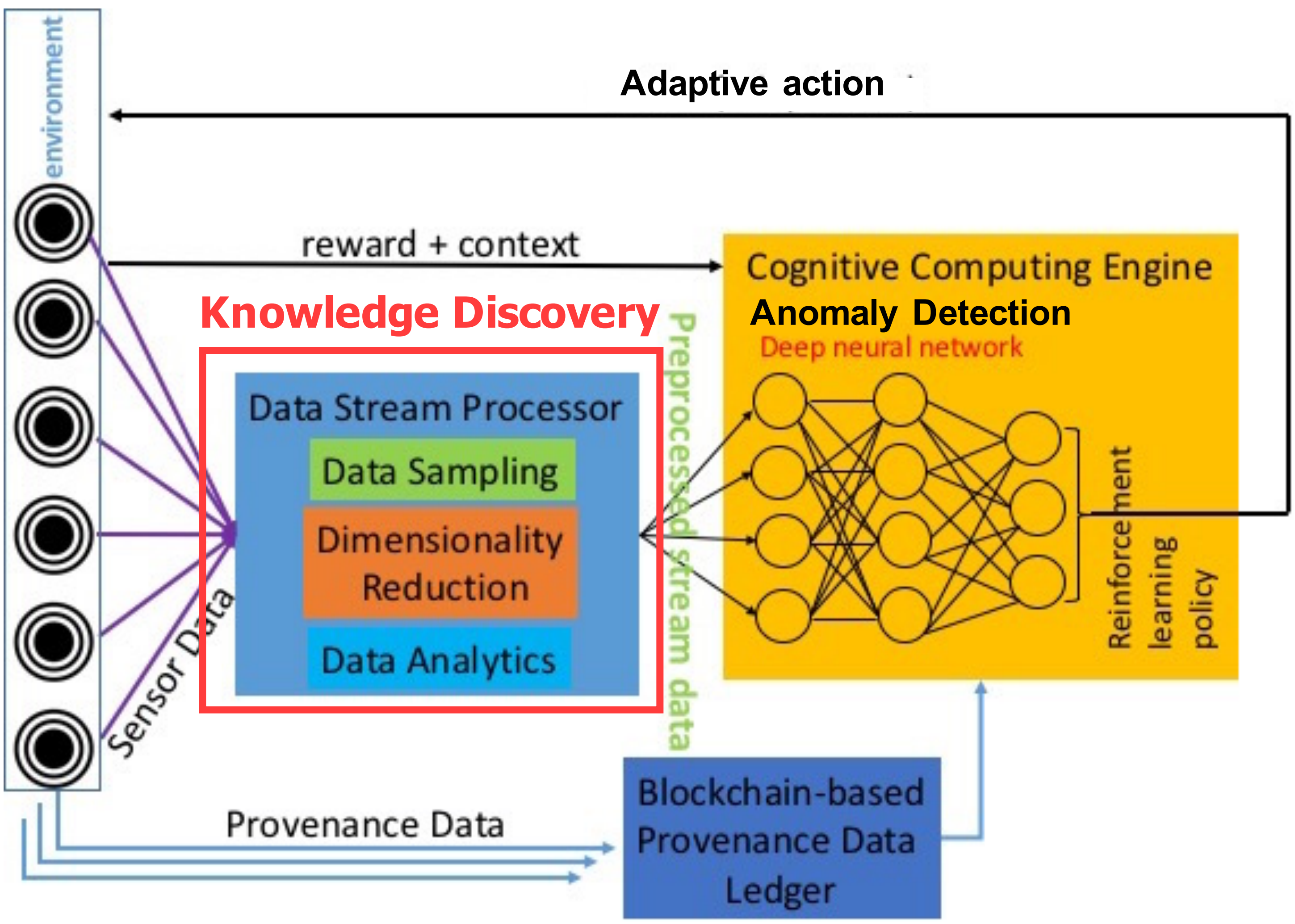
Other Deep Learning Related Projects

- **User and Entity Behavior Analytics (UEBA)**:
  - Process of obtaining the baseline of user activity and behavior to detect potential intrusions and protect from insider threats.
  - Traffic patterns of users would represent the sequences to learn.
- **Network Intrusion Detection Systems (NIDS)**:
  - The application of the DL approach is straightforward.
  - Network packets would represent the set of events to monitor in the system.

Knowledge Discovery

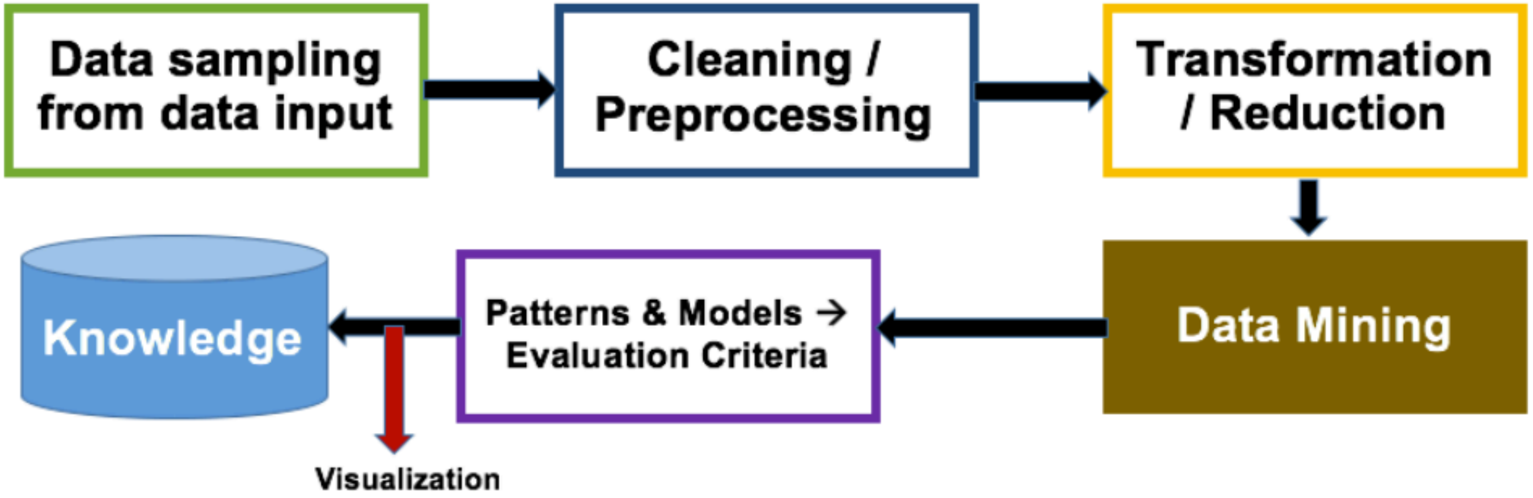
Solutions Based on Pattern Recognition

Comprehensive Architecture of IAS



Knowledge Discovery in IAS

- Knowledge discovery constitutes data transformation for processing, dimensionality reduction, and feature selection, which leads to pattern recognition and visualization.



Knowledge Discovery By Light-weight ML Algorithms

- Compared to deep learning methodologies, pattern recognition through feature extraction is one of the cost effective methodologies.

- Based on the best feature selection approach, light-weight machine learning algorithms such as Support Vector Machine (SVM), k-means, Random Forests, and K-Nearest Neighbors (KNN) can be very efficient.

- Features can be selected through Filter methods (scoring each feature), Wrapper methods (set of features as a search problem), or embedded methods (learning features on-the-fly).

Knowledge Discovery – Inference Models

- Hidden Markov Models (HMM) can be used to infer the probability of observed sequences, probability of latent variables, and statistical significance.

- Models such such as these cannot handle large sequences of data but for limited data, HMMs are better preforming than deep learning methodologies.

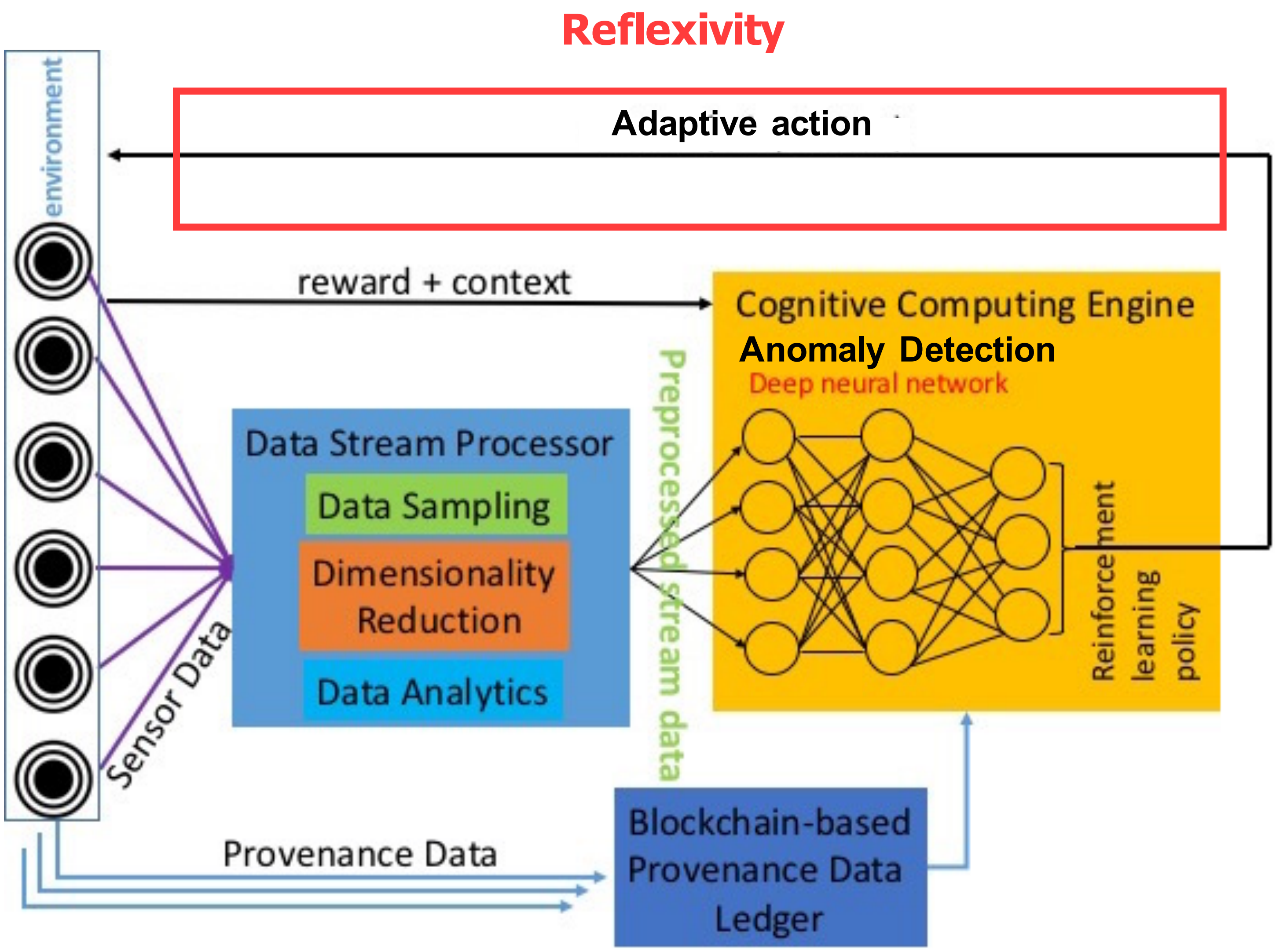
- Similarly, Bayesian inference functions as the probability update function as the new data (or context) comes to light.

- In our reflexivity module, we used Bayesian inference model to update the probabilities.

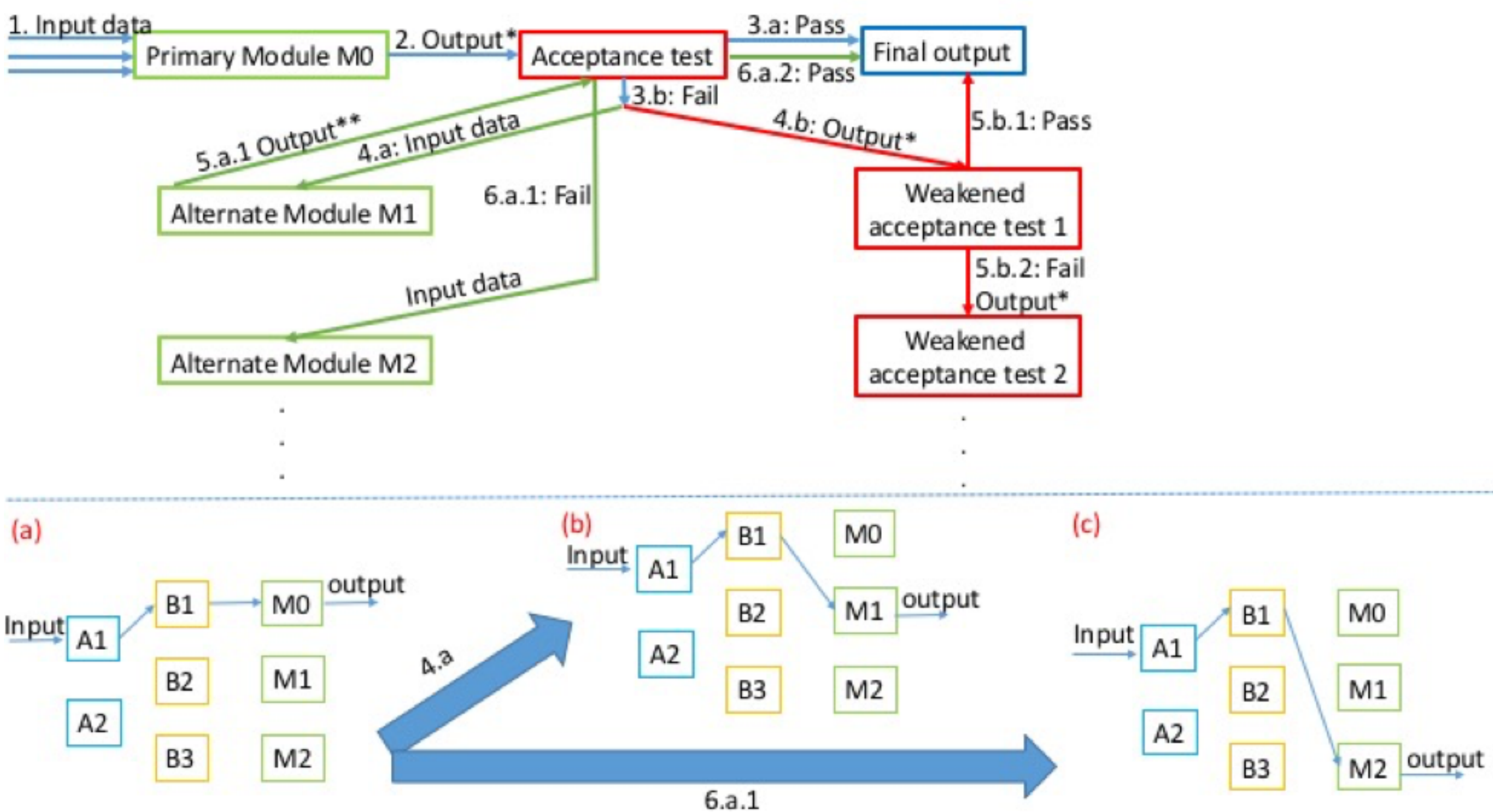
Reflexivity

A Solution Based on Graceful Degradation

Comprehensive Architecture of IAS



Generic Model of Dynamic Adaptation



Problem Statement

Given a smart cyber system operating in a distributed computing environment, it should be able to:

1. Replace anomalous/underperforming modules

2. Swiftly adapt to changes in context

3. Achieve continuous availability even under attacks and failures.

Graceful Degradations: Combinatorial Replica Replacement Scheme

- Combinatorial Structure is a subset satisfying certain conditions.

- Each block contains systems and their replicas that are mathematically distributed.

- The systems and their replicas in the distributed blocks are strategically connected to receive updates from primary modules.

- Resources are mathematically balanced, enabling scalable designs for the systems.

(7, 7, 3, 3, 1)-configuration

- 7 systems $\{S_1, S_2, S_3, S_4, S_5, S_6, S_7\}$
- 7 Distributed Autonomous Blocks (DABs) each with 3-system subset

$$DAB_1 = \{S_1, S_5, S_7\}, DAB_2 = \{S_1, S_2, S_6\},$$
$$DAB_3 = \{S_2, S_3, S_7\}, DAB_4 = \{S_1, S_3, S_4\},$$
$$DAB_5 = \{S_2, S_4, S_5\}, DAB_6 = \{S_3, S_5, S_6\},$$
$$DAB_7 = \{S_4, S_6, S_7\}.$$

(7, 7, 3, 3, 1)-configuration

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- Each system appears in 3 DABs (Say, S_6)

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- 7 systems $\{S_1, S_2, S_3, S_4, S_5, S_6, S_7\}$
- 7 Distributed Autonomous Blocks (DABs) each with 3-system subset
- Each system appears in 3 DABs
- Each pair of systems appear in 1 DAB (Say, S_1 and S_5)

$$\boldsymbol{DAB_1} = \{\boldsymbol{S_1}, \boldsymbol{S_5}, S_7\},\ DAB_2 = \{S_1, S_2, S_6\},$$
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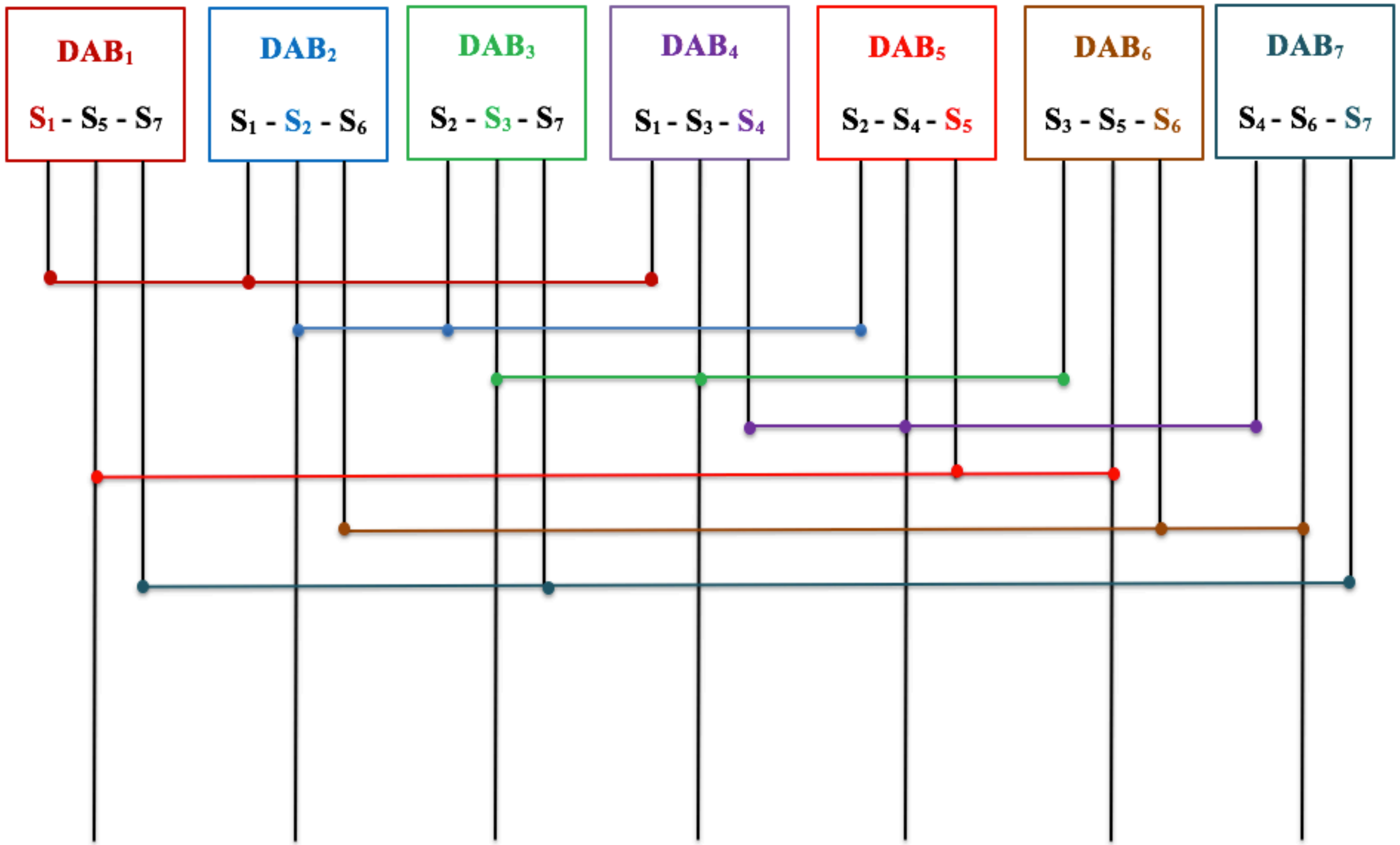
(7, 7, 3, 3, 1)-configuration

- 7 systems $\{S_1, S_2, S_3, S_4, S_5, S_6, S_7\}$ **M**
- 7 Distributed Autonomous Blocks (DABs) **A**
- each with 3-system subset **C**
- Each system appears in 3 DABs **R**
- Each pair of systems appear in 1 DAB **O**

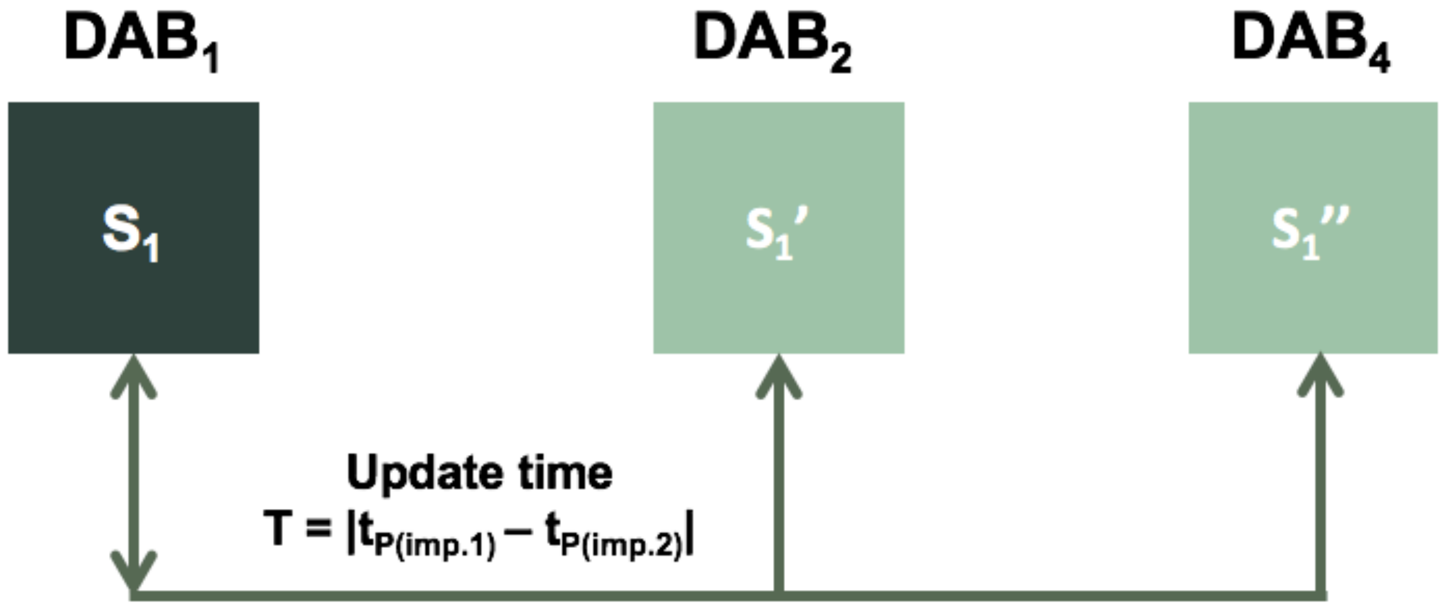
The configuration (M, A, C, R, O) = (7, 7, 3, 3, 1)

(7, 7, 3, 3, 1)-configuration
DAB: Distributed Autonomous Block



(7, 7, 3, 3, 1)-configuration

- Each primary module periodically updates its replicas in corresponding distributed block connected by communication links (CC).



- Update the interval dynamically through learning models with Bayesian learning by continuously updating the prior.

(7, 7, 3, 3, 1)-configuration

- Update time is defined as

  P_I(importance (I) | operational context (C)) = $\frac{P(C|I)P(I)}{P(C)}$

  Update interval T = | $t^1_{P(I)} - t^2_{P(I)}$ |

- Operational Context can be set dynamically and importance is a binary classifier (important /not important)

- When any system in any primary module's DAB acts in anomalous fashion, that system can be
  - Replaced with one of the replicas that can be selected in round robin fashion.
  - Anomalous module will be set for self-healing or repair by external source

(7, 7, 3, 3, 1)-configuration

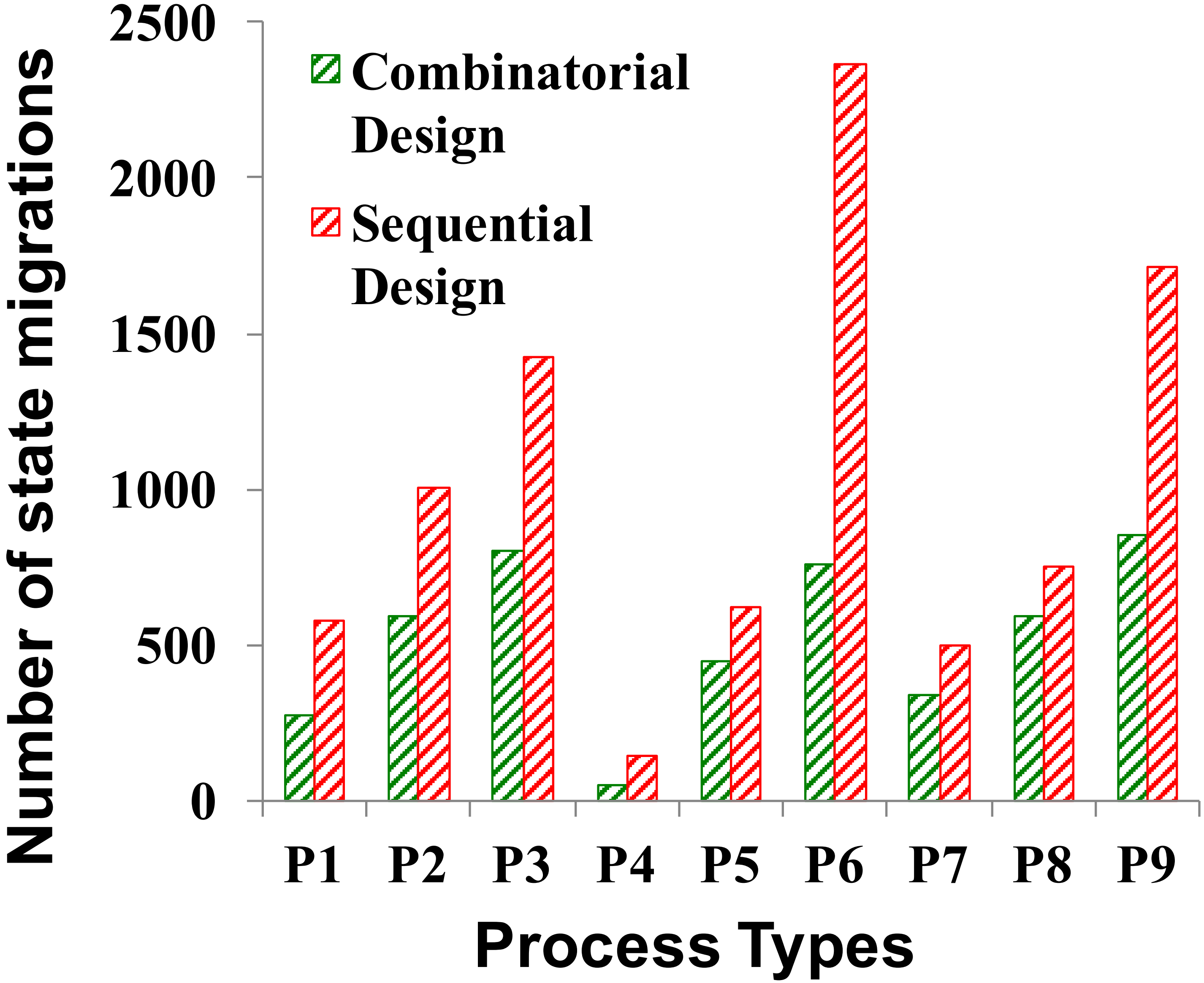
- The prototype is built with FAYE framework[1] with Node.js.
- It is a server-client framework where servers act as primary modules and clients as replicated system.
- Replica updates are done through a combinatorial design simulator[2].
- Combinatorial simulator is loaded with finite processes to compare the updates and processing time compared to a regular or sequential processing.

[1]https://faye.jcoglan.com/node.html [2]https://goo.gl/pgVHdk

Measurements for Various Process Completions

Process Type	Process Name	**Speed Up Due to Combinatorial Replica Scheme** (Compared to regular sequential design)
P1	FIBSEARCH	1.3
P2	DOUBLE MULT	1.4
P3	FIBB	1.5
P4	SEARCH	1.8
P5	COPY	1.8
P6	SCALAR	2
P7	SUM	2.1
P8	PRINT	3
P9	MOVEMENT	3.1

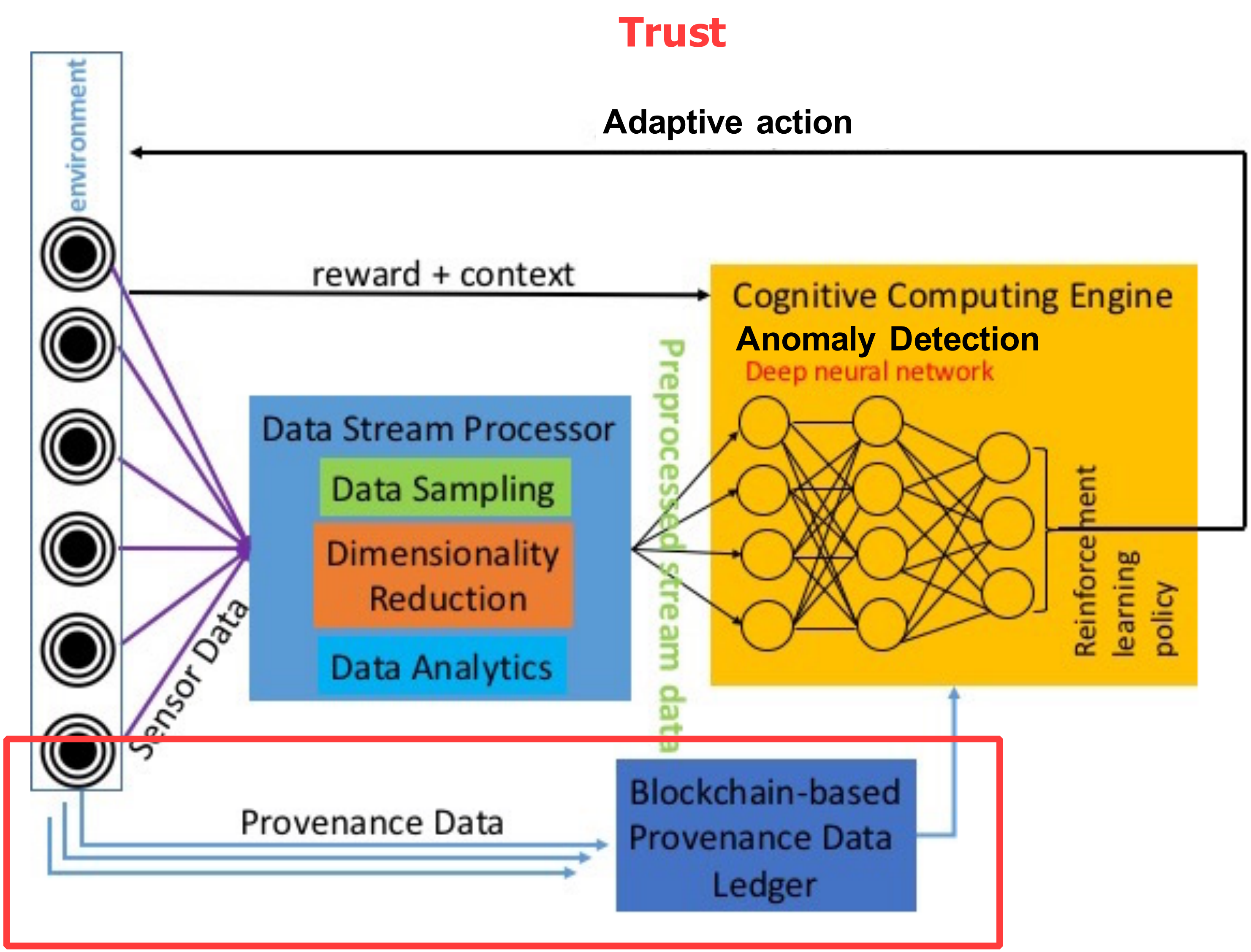
Measurements for Various Process Completions



Trust

A Solution Based on Blockchain

Comprehensive Architecture of IAS



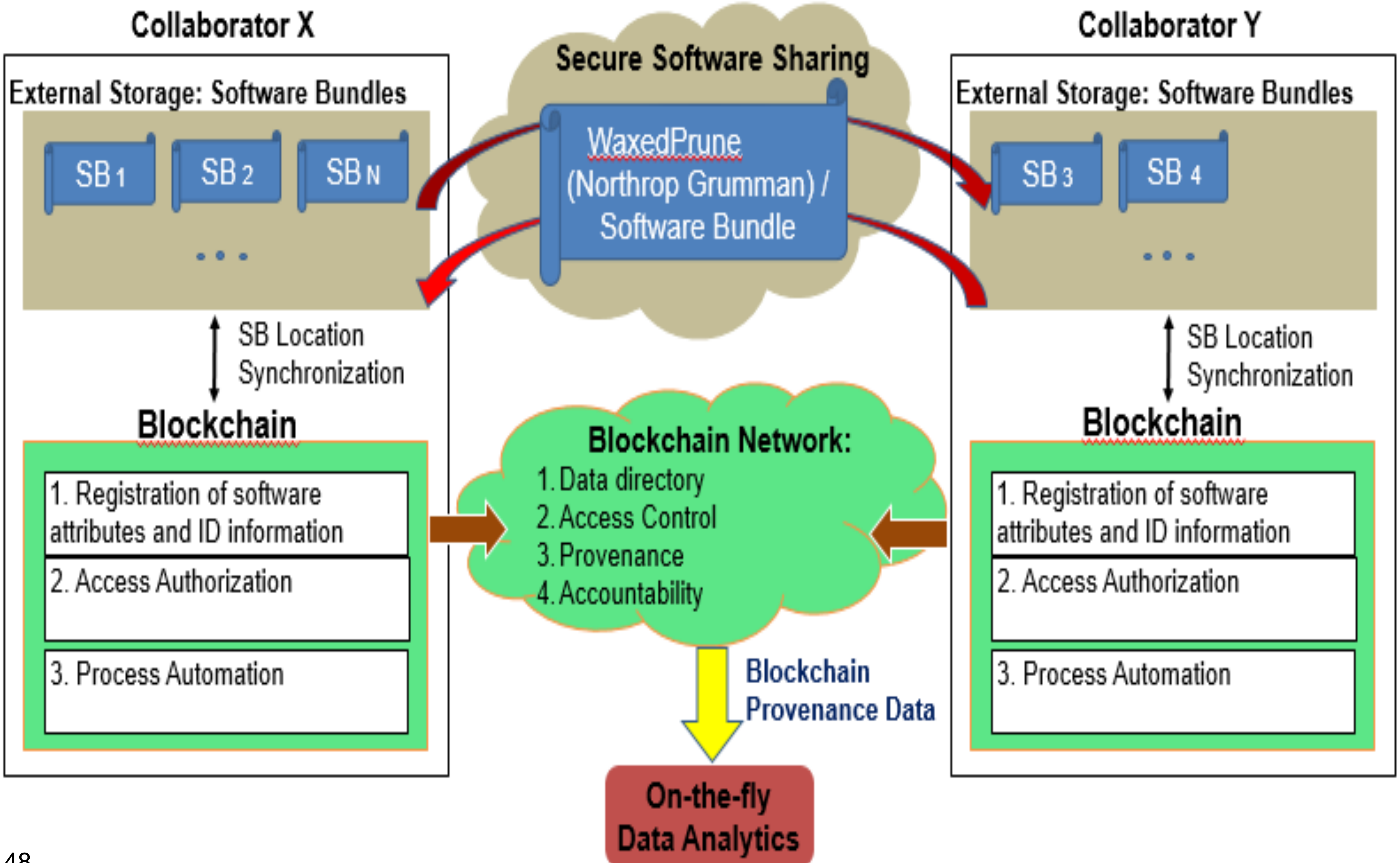
Problem Statement

- Provide trust (integrity, confidentiality, verifiability) to provenance data in IAS
  - Interactions between services are logged
  - Log records can not be corrupted
- Provide trust for network participants in IAS
  - Ensure data confidentiality
  - Ensure data integrity
- Provide privacy-preserving data exchange in IAS

Blockchain Technology Deployment

- Fine-grained role-based and attribute-based access control with data leakage detection capabilities is provided by integration with 'WAXEDPRUNE'
- Performance improvements:
  - Depth-robust graphs to store blockchain for faster transaction verification: no need to verify all the links in the chain

Blockhub: blockchain-platform for IAS



Future Work

- Develop cyber attribution techniques with machine learning to enhance the forensics and malware detection.

- Optimize the reflexivity property's replacement policy with distributed voting and Hidden Markov Model to determine update interval.

- Failure recovery for blockchain framework with mobile environments.

References:

1. Mani, Ganapathy, Bharat Bhargava, and Basavesh Shivakumar. "Incremental Learning Through Graceful Degradations in Autonomous Systems." In *2018 IEEE International Conference on Cognitive Computing (ICCC)*, pp. 25-32. IEEE, 2018.

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Thank you!!!