



# **CHARIOT – 3<sup>rd</sup> Workshop** Thursday 22 October 2020 (online)

## IOT DATA SECURITY AND PRIVACY SOLUTIONS – CHALLENGES AND OPPORTUNITIES FOR AIRPORTS

# IoT Privacy, Security and Safety Supervision Engines

Magdalena Kacmajor Senior Applied Researcher IBM Ireland

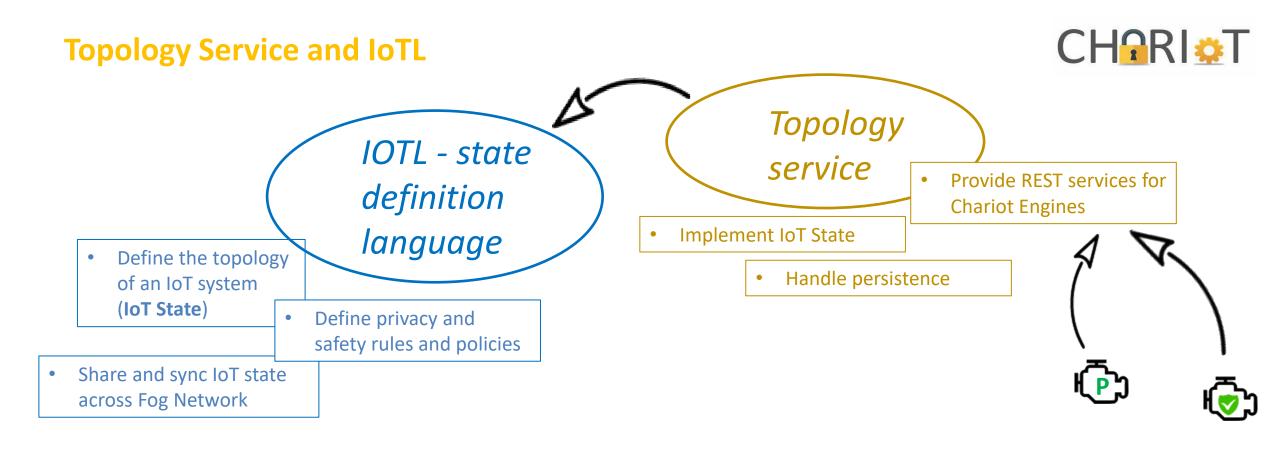
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## **IPSE: IoT Privacy, Security and Safety Supervision Engines**

- A set of novel runtime components acting in concert to understand and monitor the cyber-physical ecosystem
  - Privacy Engine: privacy by design
    - -> handling data encryption policies based on blockchain technologies
  - Security Engine: firmware authentication
    - -> identification of security vulnerabilities, rule-based filtering and validation with blockchain
  - Safety Supervision Engine: safety policies enforcement:
    - -> monitoring data streams with machine learning deployed on the edge
- Topology service and IoT Language
  - Enable functionality of the Privacy and Safety Supervision Engines
- Predictive Analytics for anomaly detection







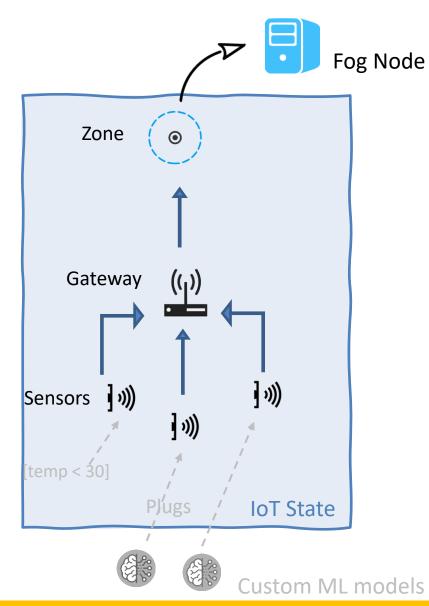


- Concise but comprehensive representation of current state
- Easy to share across the Fog Network
- Easy to sync to ensure consistent state
- Easy to store and recover
- Easy to interact with via REST interface



## **Topology Service and IoTL**

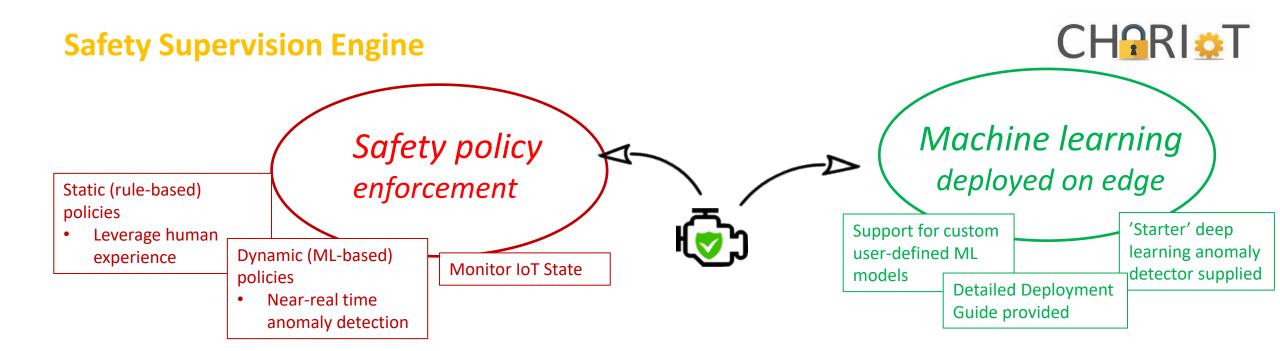




#### **CORE SPECIFICATIONS**

- Entities
  - Zones
  - Gateways
  - Sensors
- Relations: Defined between two components in the system.
  - Dependency, correlation, equality, delayed condition...
- Safety policy definition
  - Enforcements
  - Plugs
- Privacy policy definition:
  - Access Control Lists,
  - Schemas
  - Anonymization





Stream Listener: Monitor, assess and enforce

Integration of dynamic (ML-based) policies and user-defined rules

## Plug & Play Machine Learning: easily upload custom models

Safety supervision without manual effort – does not require time

Web interface for registering and enforcing safety policies

Detect & Predict safety policy violations with associated Alert

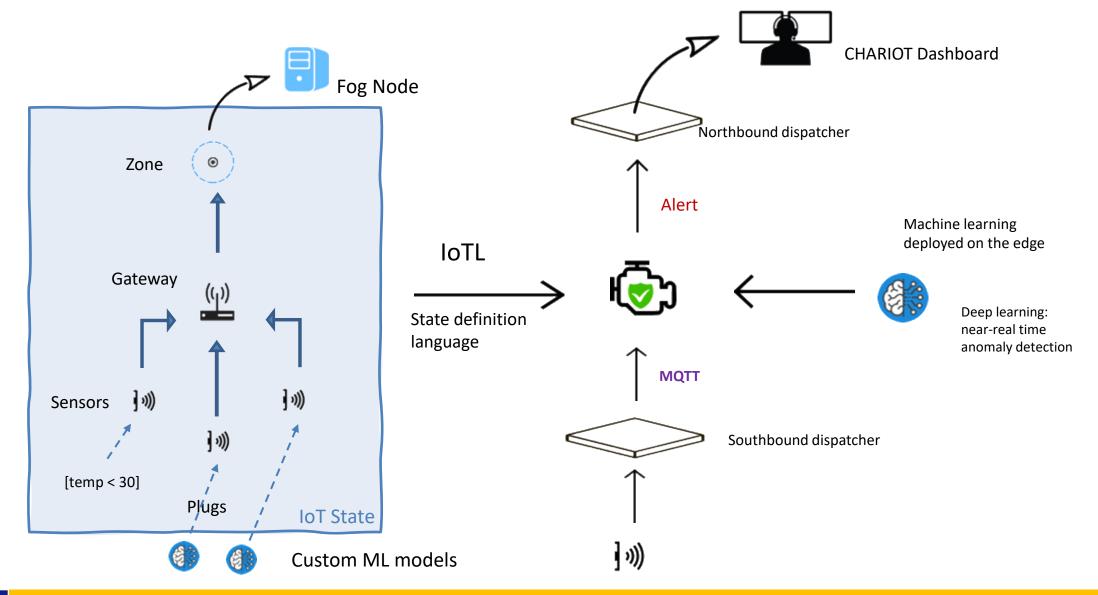
- or expert knowledgeMachine Learning deployed on edge
- Of-the-shelf Deep Learning anomaly detector provided



Generation

### **Safety Supervision Engine and Anomaly Detection**







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## **Safety Supervision Engine and Anomaly Detection**



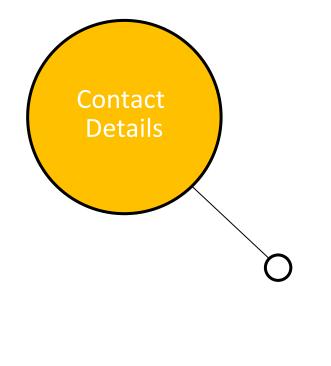
#### Integration with CHARIOT Dashboard

- Complete REST API provided for safety policy management and anomaly detectors configuration
- CHARIOT Dashboard provides user-friendly GUI
- Alternatively, safety policies can be managed through IoT Manager UI

Enforce Policy Dynamic Static Static policy *Zone designstudio	Upload model  File  Model name  Model class	basic_litm.35 (144.23 KB)		Enforce Policy Dynamic Static Dynamic policy *Zone designstudio
*Device device_52806c75c3fa_Sensor1 V		Add plug Zone designstudio	~	<pre>*Plug device_52806c75c3f2_Sensor5.terr   *  Priority 2 *</pre>
<pre>enforce [device_52806c75c3fa_Sensor1.hum &lt; 15]</pre>		Device name device_52806c7     Metric name temp	5c3f2_Sensor5	enforce device_52806c75c3f2_Sensor5.temp
		Model name     BASIC_LSTM     Create     plug device_5	2806c75c3f2_Sensor5.	temp BASIC_LSTM (device_52806c75c3f2_Sensor:









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# CHARIOT – 4<sup>th</sup> Plenary Meeting Wednesday 30 September 2020 (online)

# **Privacy Engine and Data Encryption**

Konstantinos Skianis PhD Senior Researcher CLMS

CHARIOT – 4<sup>th</sup> Plenary Meeting, 30 September 2020

### **Privacy Engine and Data Encryption - Intro**

# **CH**RIOT

#### Main goals

- Protect private and sensitive data
- Identify types of sensors and services with regards to privacy
- Components communicate without exposing sensitive information

#### **Novel aspects**

- Anonymization methods
- Cognitive: use machine learning models for disseminating messages
- Provides insight on privacy threats based on topology information
- Self-contained service deployed on a Fog node

#### Main benefits

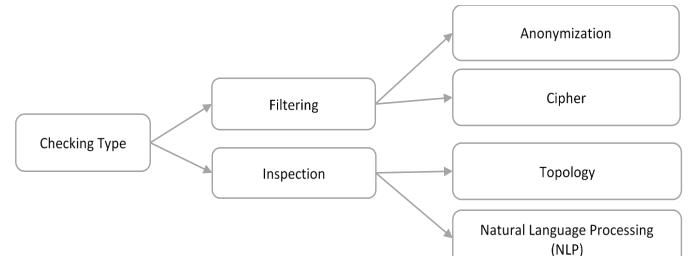
- Create value from IoT sensor messages by training specialized dissemination classification models
- A complete framework for managing private data in industrial IoT environments



## **Privacy Engine and Data Encryption**



- Two types of checks enables passive and active safeguarding
- Inspection checks helps administrator of IoT network to actively map all privacy related information during configuration setup
- Filtering safeguards information exchange with other parties by encrypting and anonymizing information

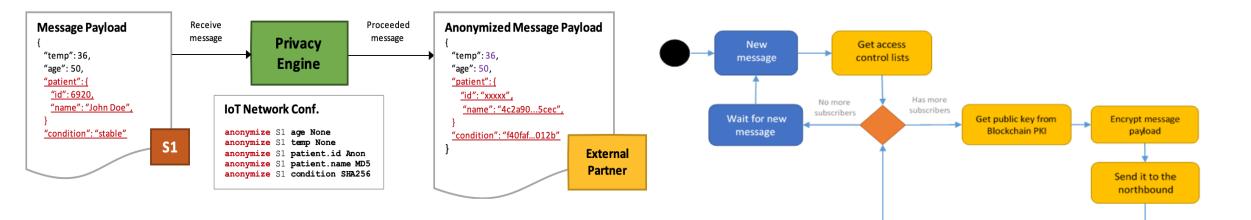


IoTL Statement	Description	
define SENSOR S1params {"privacySensitive": 1.0}	Mark a sensor as privacy sensitive.	
acl BMS S2 DENY acl BMS S2 ALLOW	Safeguard access to sensor messages	
schema EmployeeIDpattern "\d{4}-\d{4}- \d{4}\d{4}"private expect S1 EmployeeID	Manually define privacy sensitive formats.	
anonymize S1 age SHA256	Enable privacy engine to anonymize age on message originated from S1 Sensor.	



## **Privacy Engine and Data Encryption**





#### Anonymization

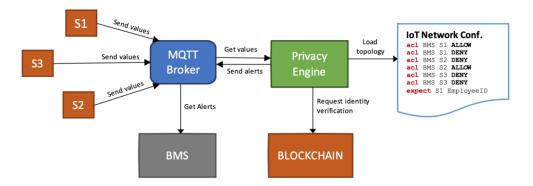
- Administrator defines message fields to be anonymized
- Engine applies anonymization logic on messages originating from specific tables
- Anonymization replaces value with random sized string of '\*'
- MD5 & SHA256 pseudo-anonymizes data by returning hashed value

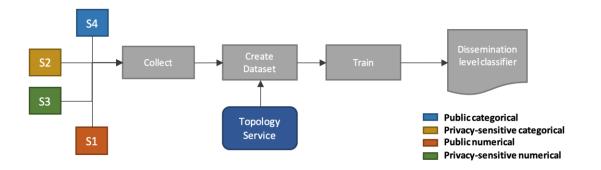
#### Encryption

- Prevents sensitive information leakage to unauthorized users
- Public Key encryption adds end to end encryption between Fog Node and External services preventing MitM attacks
- Access control lists defined by the CHARIOT by using IoTL guards user data



## **Privacy Engine and Data Encryption - Standalone**





CHARIOT

#### Manual private data guard

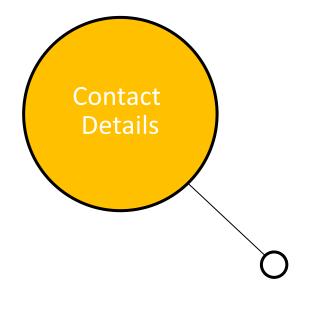
- Provides insight on privacy threats based on topology information
- Topology information can be pulled by API
- Information can also be pulled by local file created by Administrator, to achieve standalone functionality (without the platform API)
- This version can be installed in single board Linux PC and connected to external MQTT broker to receives messages per configuration

#### **Cognitive - Detect privacy violation by using dissemination level classifier**

- Collection of messages from every sensor is used to produce datasets for model training
- Message types stemming from private sensors are used to compose attributes of training instance
- Machine learning to produce Dissemination level classifier
- Fully automated process, variable reliability









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# CHARIOT – 3<sup>rd</sup> Workshop Thursday 22 October 2020 (online)

# **Predictive Analytics for Out-of-Bounds Behaviour**

Kostas Zavitsas PhD VLTN

CHARIOT – 4<sup>th</sup> Plenary Meeting, 30 September 2020

### **Predictive Analytics for Out-of-Bounds Behaviour**



- Technical objectives:
  - 1. Identify sources of variation in a monitored system
  - 2. Datasets of varying dimensions capturing a stochastic real-world processes
  - 3. Calculate bounds of normal behavior
- Business objectives:
  - robust/ context agnostic
  - efficient/ no human intervention

All 3 Chariot case studies offer ample datapoints and opportunities to train accurate ML based predictive models



Locomotive / Fleet – DMMS



Smart Building/ Technology campus – BMS & Security IoT





### **Predictive Analytics for Out-of-Bounds Behaviour**

**CHRIOT** 

- Anomaly Detection component pipeline:
  - Part 1: Training
    - Data preprocessing
      - Temporal resampling
    - Normalization and regularization to avoid overfitting to one feature
    - Cross validation algorithm used with k=10
    - Unsupervised machine learning clustering models
      - Elliptic Envelope (EE)
      - Isolation Forest (IF)
      - One Class Support Vector Machine (OSVM), and
      - Density-based spatial clustering of applications with noise (DBSCAN)
    - model evaluation assessed with the Fowlkes-Mallows index (FM)

$$FM = \sqrt{\frac{TP}{TP + FP} * \frac{TP}{TP + FN}}$$

- Update dashboard information
- Upload model to Security Engine



- Collect live data
- Check if out of bounds behaviour

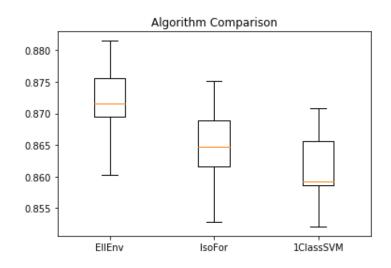


## **Predictive Analytics for Out-of-Bounds Behaviour**

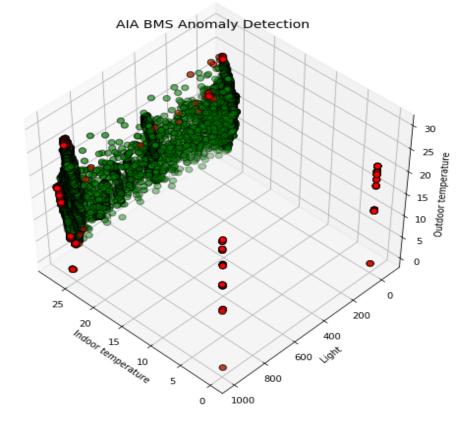
# **CHRIOT**

Unsupervised AD modelling



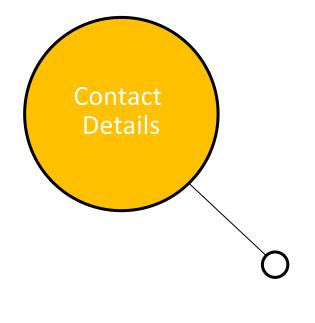


- Best performing model:
  - Elliptic Envelope with 97% prediction accuracy for incorrect Indoor temperature readings











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