DATA PROVENANCE FOR INTERNET OF THINGS (IOT)

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Abstract

The concept of Internet of Things (IoT) offers immense benefits by enabling devices to leverage networked resources thereby making more intelligent decisions. The numerous heterogeneous connected devices that exist throughout the IoT system creates new security and privacy concerns. Some of these concerns can be overcome through data trust, transparency, and integrity, which can be achieved with data provenance. Data provenance, also known as data lineage, provides a history of transactions that occurs on a data object from the time it was created to its current state. Data provenance has been explored in the areas of scientific computing and business to track the workflow of processes, as well as in the field of computer security for forensic analysis and intrusion detection. Data provenance has immense benefits in detecting and mitigating current and future malicious attacks.

In this dissertation proposal, we explore the integration of provenance within the IoT architecture. We take an in-depth look at the creation, security and applications of provenance data in mitigating malicious attacks. We define our model constructs for representing IoT provenance data. We propose a provenance aware system that collects provenance data in an IoT framework. We focus on a holistic approach in which provenance information is represented at all layers of the IoT architecture. This system ensures trust and helps establish causality for decisions and actions taken by an IoT connected system. However, there are existing issues with devices running memory space, and this is attributed as a consequence of the amount of data generated by our data provenance collection system, as well as resource constrains on low memory embedded systems. To address these issues, we propose a framework that provides an efficient storage of provenance data contained in an IoT architecture. Adopting a policy approach for provenance collection allows flexibility in deciding what provenance data to collect. It also helps address the issue with memory constraint of collecting provenance data in IoT devices. We evaluate the effectiveness of

our proposed framework by looking at an application of provenance data for the security of malicious attacks. We focus on evaluation using an intrusion detection system, which detects malicious threats that exists in an IoT framework.

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Chapter 1

Introduction

1.1 Motivation

In recent years,the Internet of Things(IoT) has gathered significant traction which has led to the exponential increase in the number of devices connected to the internet. According to a report released by Cisco [14], it is estimated that a total of 50 million devices will be connected to the internet by the year 2020. Data is generated in an enormous amount in real-time by sensors and actuators contained in these devices. With the vast amounts of connected heterogeneous devices, security and privacy risks are increased. Rapid7 [35], an internet security and analytics organization, released a report highlighting vulnerabilities that exist on select IoT devices. In their report, they outline vulnerabilities in baby monitors which allowed intruders unauthorized access to devices whereby a malicious intruder can view live feeds from a remote location. Having a provenance aware device will be of immense benefit to the security of the device since it ensures trust between interconnected devices. With provenance information, we can generate an activity trail which can be further analyzed to determine who, where, and how, a malicious attack occured in order to provide preventive measures to eradicate future or current attacks. [13].

In an IoT system, most of the interconnected heterogeneous devices (things) are embedded systems which require lightweight and efficient solutions as compared to general purpose systems. This requirement is attributed to the constrained memory and computing power of such devices. The vast amount of data generated from IoT devices requires stronger levels of trust which can be achieved through data provenance. Provenance is used to determine causality and effect of operations performed on data objects [17]. Data provenance ensures authenticity, integrity and transparency between information disseminated across an IoT system. This level of transparency can be translated to various levels across the IoT architectural stack. To achieve transparency in an IoT framework, it is imperative that data provenance and IoT systems be unified to create a provenance aware system that provides detailed records of all data transactions performed on devices connected in an IoT network.

Most provenance-aware systems collect a fixed amount of provenance data(e.g system calls, files, and process) [24, 6, 17]. There is a need to create provenance-aware systems which allows for the flexibility in provenance data collection. By doing this, we provide pruning [11] of provenance data that is unrelated to a specific organization's requirements. Policy specification and implementation details are discussed in greater detail in chapter 4.

1.2 Provenance-Aware IoT Device Use Case

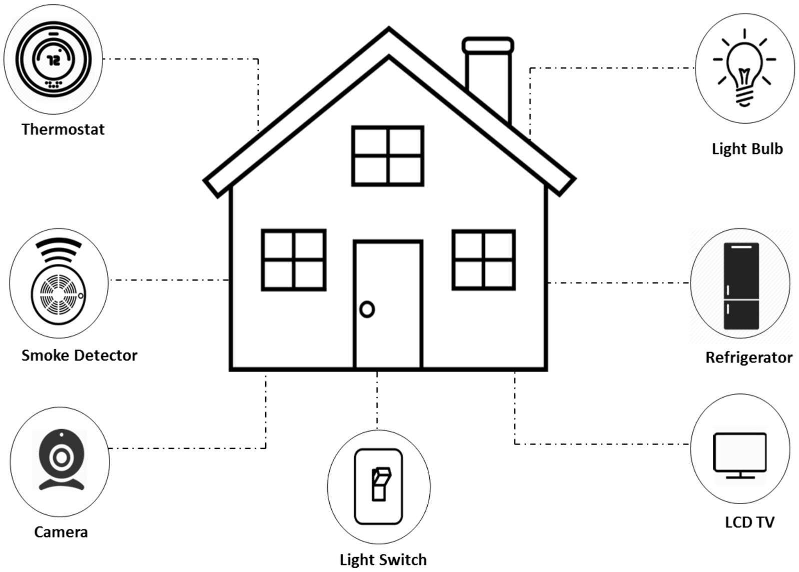


Figure 1.1: Smart home use case Diagram

Consider a smart home as illustrated in figure 1.1 that contains interconnected devices such as a thermostat which automatically detects and regulates the temperature of a room based on prior information of a user's temperature preferences, a smart lock system that can be controlled remotely and informs a user via short messaging when the door has been opened or is closed, a home security camera monitoring system, a smart fridge which sends a reminder when food produce are low. In an event that a malicious intruder attempts to gain access to the smart lock system and security camera remotely, provenance information can be used to track the series of events to determine where and how a malicious attack originated. It can also be used as a safeguard to alert of a possible remote or insider compromise thereby protecting against future or current malicious attacks.

1.3 Research Questions

The unification of data provenance and IoT is essential to the security of data disseminated in an IoT system. Data provenance and IoT are two essential components that need to be unified. However, the unification of data provenance and IoT raises some important research issues some of which are as a result of pre-existing provenance and IoT related issues. Some of the issues raised as a result of the unification of data provenance with IoT are outlined below:

- Memory constraints on IoT Devices: The vast amounts of data generated leads to high storage space utilization. Proper memory management and data pruning techniques should be employed for efficient storage of provenance data on memory constrained devices.

- A fundamental question exists in effective modeling of provenance data. How do we model provenance data collected from sensors and actuators contained in IoT devices? Are there models used to represent causality between sensor and actuator readings in the IoT architecture.

- How do we effectively collect provenance data in resource constrained devices and relate this information across various layers of the IoT architecture

1.4 Research Contribution

In this dissertation, we propose the following key contributions:

- A provenance collection framework which represents causality and dependencies between entities contained in an IoT system. This system creates groundwork for capturing and storing provenance data across the IoT architectural stack.
- An efficient algorithm for storing provenance data on IoT devices. We evaluate our contributions for an efficient provenance storage system by using an intrusion detection system on IoT devices.

1.5 Organization of Dissertation proposal

The remaining portion of this dissertation proposal is organized as follows. In Chapter 2, we present background information on data provenance and the Internet of Things. We also discuss models for representing provenance data and an overview of relevant compression techniques. In Chapter 3, we outline the literature review on the state of the art on provenance collection in file systems, scientific workflow and database systems. In Chapter 4, we discuss our proposed provenance collection system. We also describe our model construct for representing provenance data cross the IoT architecture. In Chapter 5, we describe our framework for efficient storage of provenance data. Finally, in Chapter 6, we conclude the proposal with proposed future work.

Chapter 2

Background Information

This chapter describes key concepts of data provenance, IoT characteristics, and provenance models. It outlines differences that exists between provenance, log data and metadata.

2.1 Data Provenance

The Oxford English dictionary defines provenance [32] as "the place of origin or earliest known history of something". An example of provenance can be seen with a college transcript. A transcript can be defined as the provenance of a college degree because it outlines all of the courses satisfied in order to attain the degree.

In the field of computing, data provenance also known as data lineage can be defined as the history of all transformations performed on a data object from its creation to its current state. Cheney et al [13] decribes provenance as the origin and history of data from its lifecycle. Buneman et al [12] describes provenance from a database perspective as the origin of data and the steps in which it is derived in the database system. We formally define provenance as follows:

Definition 1 *Data provenance of an object is a comprehensive history of transformations that occurs on that object from its creation to its present state.*

Provenance involves two granularity levels: fine-grained provenance and coarse-grained provenance. Fine-grained provenance [17] entails the collection of a detailed level of provenance. Coarse grained provenance, on the other hand, is a collection of a summarized version of provenance. Data provenance has immense applications and has been explored in the areas of scientific computing [18, 6] to track how an experiments are produced, in business to determine the work-flow of a process, and in computer security for forensic analysis and intrusion detection [8, 29, 28] . Provenance denotes the who, where and why of data [13]. An example of provenance for a software system is a web server's log file. This file contains metadata for various request and response time and the ip address of all host systems that requests information from the server. Provenance data is represented as an acyclic graph which denotes casual relationship and dependencies between entities.

Provenance ensures trust and integrity of data [10]. It outlines causality and dependency between all objects involved in the system and allows for the verification of a data source. Causality and dependency are used to determine the relationship between multiple objects. This information in turn can be used in digital forensics [39] to investigate the cause of a malicious attack and also in intrusion detection systems to further enhance the security of computing devices.

2.1.1 Provenance Characteristics

Since provenance denotes the who, where and why of data transformation, it is imperative that data disseminated in an IoT architecture satisfies the required conditions. The characteristics of data provenance are outlined in detail below.

- Who: This characteristic provides information on who made modifications to a data object. Knowing the "who" characteristic is essential because it maps the identity of modification to a particular data object. An example of who in an IoT use case is a sensor device identifier.

- Where: This characteristic denotes location information in which data transformation was made. This provenance characteristic could be optional since not every data modification contains location details.

- When: This characteristic denotes the time information in which data transformation occurred. This is an essential provenance characteristic. Being able to tell the time of a data transformation allows for varied use scenarios of tracing data irregularities.

- What: This characteristic denotes the process in which transformation is applied on a data object. A use case for IoT can be seen in the various operations(create, read, update, and delete) that could be performed on a file object.

2.2 Internet of Things (IoT)

There is no standard definition for IoT, however, researchers have tried to define the concept of connected "things". The concept of IoT was proposed by Mark Weiser in the early 1990s[26] which represents a way in which the physical objects, "things", can be connected to the digital world. Gubbi et al [30] defines the IoT as an interconnection of sensing and actuating devices that allows data sharing across platforms through a centralized framework. We define (IoT) as follows:

Definition 2 *The Internet of Things (IoT) is a network of heterogeneous devices with sensing and actuating capabilities communicating with each other thereby enabling each devices become smarter through data analytics and computation.*

The notion of IoT has been attributed to smart devices. The interconnectivity between various heterogeneous devices allows for devices to share information in a unique manner. Analytics is the driving force for IoT. With analytics, devices can learn from user data which in turn can be used to make smarter device decisions. This notion of smart devices is seen in various commercial applications such as smartwatches, thermostats that automatically learns a user patterns, . The ubiquitous nature of these devices make them ideal choices to be included in consumer products.

With the recent data explosion [23] due to the large influx in amounts of interconnected devices, information is disseminated at vast rate and with this increase involves security and privacy concerns. Creating a provenance-aware system is beneficial to IoT because it ensures the trust and integrity of interconnected devices. Enabling provenance collection in IoT device allows devices to capture valuable information which enables backtracking in an event of a malicious attack. We take a holistic approach to provenance collection by looking at how provenance information is collected across an IoT architectural framework.

2.2.1 IoT Architecture

IoT architecture represents a hierarchical view of how information is disseminated across multiple layers contained in an IoT framework; from devices which contains sensing and actuating capabilities to massive data centers(cloud storage). Knowing how information is transmitted across various layers allows a better understanding on how to model the flow of information across various actors contained in an IoT hierarchy.

The IoT architecture consists of four distinct layers: The sensor and actuator layer, device layer, gateway layer and the cloud layer. Figure 2.1 displays the IoT architecture and the interactions between the respective layers. The base of the architectural stack consist of sensors and actuators which gathers provenance information and interacts with the device layer. The device layer consists of devices(e.g mobile phones,laptops,smart devices) which are responsible for aggregating data collected from sensors and actuators. These device in turn forwards the aggregated data to the gateway layer. The gateway layer is concerned with the routing and forwarding of data collected from the device later. It could also serve as a medium of temporal storage and data processing. The cloud layer is involved with the storage and processing of data collected from the gateway layer. Note that the resource constraints decreases up the architectural stack with the cloud layer having the most resources(memory, computation) and the sensor layer having the least amount of resource capability.

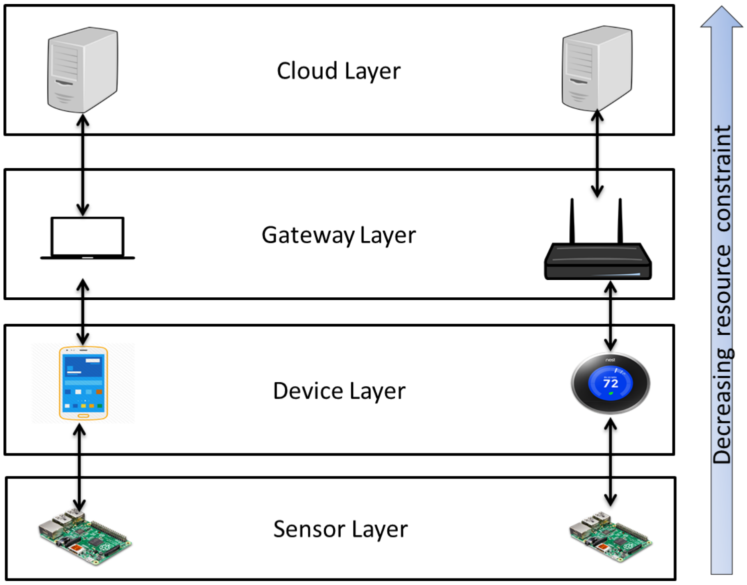


Figure 2.1: IoT Architecture Diagram.The arrows illustrates the interaction between data at various layers on the architecture.

2.3 Comparison of Provenance with Log data and metadata

Provenance data, log data and metadata are key data concepts that often are used interchangeably. We try to address the difference and similarities that might exist between provenance data, metadata and log data.

2.3.1 Provenance and Metadata

Metadata and provenance are often considered related but yet subtle exists. Metadata contains descriptive information about data. Metadata can be considered as provenance when there exists relationship between objects and they explain the transformation that occurs. For example, a web server can have metadata information such as the host and the destination IP address which might not be considered as provenance information for a specific application. It could also contain timestamps with location of IP addresses which could be considered provenance information. In summary, metadata and provenance are not the same, however an overlap exists. Metadata contains valuable provenance information but not all provenance information is metadata.

2.3.2 Provenance and Log data

Log data contains information about the activity of an object in an operating system or process. Log data can be used as provenance. It contains data trace specific to an application domain. Log files might contain unrelated information such as error messages, warnings which might not be considered as provenance data. Provenance allows for specified collection of information that relates to the change the internal state of an object. In summary, log data could provide insight to what provenance data to collect.

2.4 Model for representing provenance for IoT

In order to ensure that we properly represent the right kind of provenance information, we need to satisfy the who, where, how, and what of data transformations. Provenance data is represented using a provenance model, PROVDM which is represented in serialized form as JSON object. This model displays the causal relationship of data objects contained in an IoT architectural stack. In this model is contained information such as sensor readings, device name, and device information. This information is mapped into an appropriate provenance data model to allow for interoperability and visualization. There are two models for representing provenance. These models [2] have been applied in various literature and is considered a standard for representing provenance. Details on the provenance models are outlined below:

2.4.1 Open Provenance Model(OPM)

Open Provenance Model [27] is a specification that was derived as a result of a meeting at the International Provenance and Annotation Workshop (IPAW) in May 2006. OPM was created to address the need of allowing a centralized model for representing provenance data amongst various applications. It allows for interoperability between various provenance applications. The goal of OPM is to represent causality and dependency and also to develop a digital representation of provenance data regardless of if it is produced by a computer system. OPM is represented as a directed acyclic graph which denotes causal dependency between objects. The edges in the graph denotes dependencies with its source denoting effect and its destination denoting cause. The definitions of the edges and their relationships are denoted below:

- wasGeneratedBy: This edge denotes a relationship in which an entity(e,g artifact) is utilized by one or more entities(e.g process). An entity can use multiple entities so it is important to define the role.
- wasControlledBy: This edge outlines a relationship in which an entity caused the creation of another entity.
- used(Role): This edge denotes that an entity requires the services of another entity in order to execute.
- wasTriggeredBy: This edge denotes a relationship represents a process that was triggered by another process
- wasDerrivedFrom: This edge denotes a relationship which indicates that the source needs to have been generated before the destination is generated.

Objects represents the nodes of the relationship graph. There are three object contained in the OPM model: artifact, process, agent.

- artifact: An artifact represents the state of an entity. An artifact is graphically represented by a circle.

- Process: A process is an event which takes place at a particular time due to an agent or an artifact. A process is represented by a square object.

- Agent: Agents represents actors that facilitate the execution of a process. An agent is represented by a hexagon in an OPM graph.

OPM is used to represent all previous and current actions that have been performed on an entity and the relationship between each entities contained in the graph. Figure 2 represents an example of an OPM acyclic graph with all of its causal dependencies.

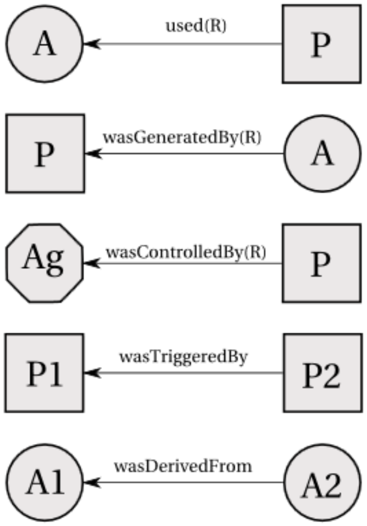


Figure 2.2: Edges and entities represented in OPM ©[27]

2.4.2 Provenance Data Model(Prov-DM)

Another model for representing provenance data is the Provenance Data Model(PROV-DM). PROV-DM is a W3C standardized extension of OPM. Prov-DM is a model that is used to depict causal relationship between entities, activities and , and agents(digital or physical). It creates a common model that allows for interchange of provenance information between heterogeneous devices. It contains two major components: types and relations.

- Entity: An entity is a physical or digital object. An example of an entity is a file system, a process, or an motor vehicle. An entity may be physical or abstract.

- Activity: An activity represents some form of action that occurs over a time frame.Actions are acted upon by an agent. An example of an activity is a process opening a file directory, Accessing a remote server.

- Agent: An agent is a thing that takes ownership of an entity, or performs an activity. An example of an agent is a person, a software product, a process.

The figure below illustrates the various types contained in PROVDM and their representation. Entities, activities and agents are represented by oval, rectangle and hexagonal shapes respectively.

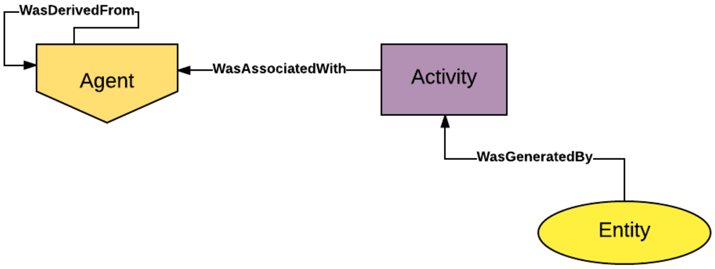


Figure 2.3: Prov-DM respresentation

Similar to the OPM, PROVDM does not keep track/estimate of future events. PROV relations are outlined below:

- wasGeneratedBy: This relation signifies the creation of an entity by an activity.

- used: This relation denotes that the functionality of an entity has been adopted by an activity.

- wasInformedBy: This relation denotes a causality that follows the exchange of two activities.

- wasDerievedFrom This relation represents a copy of information from an entity.

- wasAttributedTo: This denotes relational dependency to an agent. It is used to denote relationship between entity and agent when the activity that created the agent is unknown.

- wasAssociatedWith:This relation denotes a direct association to an agent for an activity that occurs.This indicates that an agent plays a role in the creation or modification of the activity.

- ActedOnBehalfOf: This relation denotes assigning authority to perform a particular responsibility to an agent. This could be by itself or to another agent.

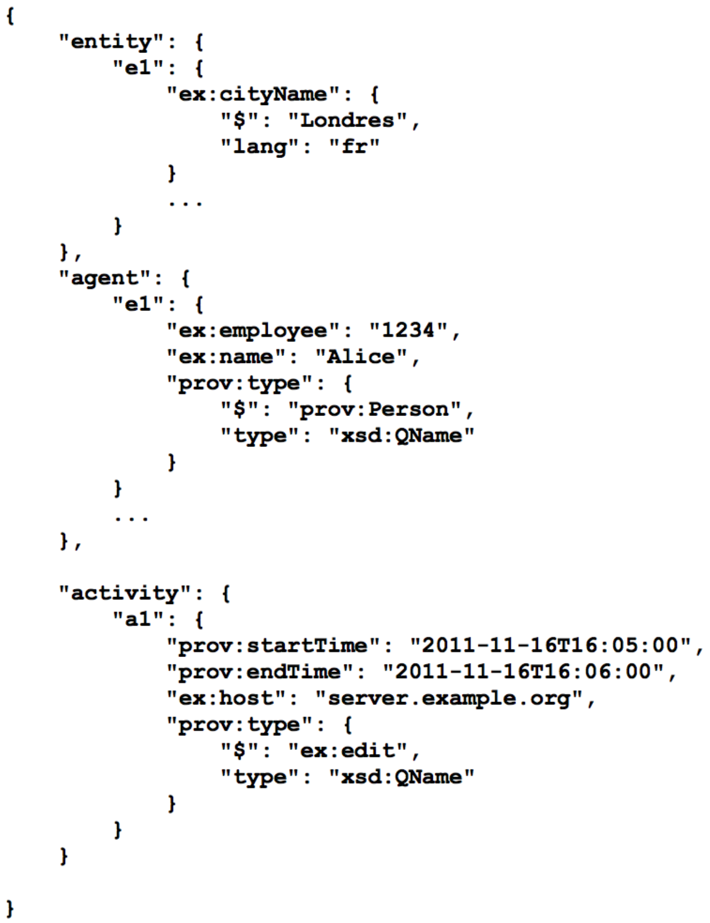
Prov-DM contains similar yet subtle differences between OPM. Some of the difference between OPM and PROVDM are described below:

- The main components Artifact, Process and Agent in the OPM model are modified to Entity, Action, and Agent.

- Additional causal dependencies such as wasAttributedTo and actedOnBelafOf were included to represent direct and indirect causal dependencies respectively between agents and entities.

2.4.3 PROV-JSON

PROV-JSON is a component of PROV-DM specification. It is used for representing PROV-DM data in JSON(Javascript Object Notation) format. It contains all of the components and relationships contained in PROV-DM. It also allows for easy serialization and deserialization of PROV-DM to JSON representation. JSON is a lightweight data format which is human readable and easy to parse. An example of PROVJSON format which includes the PROVDM types is illustrated below:



```
{
    "entity": {
        "e1": {
            "ex:cityName": {
                "$": "Londres",
                "lang": "fr"
            }
            ...
        }
    },
    "agent": {
        "e1": {
            "ex:employee": "1234",
            "ex:name": "Alice",
            "prov:type": {
                "$": "prov:Person",
                "type": "xsd:QName"
            }
        }
        ...
    },

    "activity": {
        "a1": {
            "prov:startTime": "2011-11-16T16:05:00",
            "prov:endTime": "2011-11-16T16:06:00",
            "ex:host": "server.example.org",
            "prov:type": {
                "$": "ex:edit",
                "type": "xsd:QName"
            }
        }
    }

}
```

Figure 2.4: PROV-JSON MODEL ©[4]

2.5 Overview of Relevant Compression techniques

2.5.1 Lossy Compression

Lossy compression [33] is a form of data compression in which original data can be reconstructed with some tolerance on loosing some information contained in the original data. This enables higher compression ratio than other compression techniques. Lossy Compression is mostly used in applications that do not contain strict requirements as to loosing some information. An example of a lossless compression application can be seen in an image compression software where the quality of the image is not seen by the naked eye. It is also used in speech transmission.

2.5.2 Lossless Compression

Lossless compression [33] is a data compression technique in which the original data is reconstructed without loss of any information. It can be used by applications which requires that the data is compressed and the original data be identical. An example of such an application that requires lossless compression is text compression. Any compression that alters the structure of the original text results to a different meaning of the text. For instance, the sentence “I have a black cat” would have a different meaning if any information is lost from it.

Arithmetic Coding

Arithmetic coding is a form of lossless compression which encodes a stream of characters into a variable size interval between [0,1). A probability is assigned to each characters contained in the string. A cumulative probability is used to calculate the interval of the respective character. Frequent characters are encoded with shorter codes than less frequent characters.

Chapter 3

Related Work

This section outlines some of the state of the art in the area of data provenance collection systems, data compression techniques for data provenance, and models for representing provenance data.

3.1 Related Work on Provenance Collection Systems

There has been a considerable amount of work done on data provenance collection [3, 9, 15, 29]. Some of the work done has been focused on databases, sensor networks, scientific workflow systems and file system provenance but so far little attention has been given to provenance in IoT. Some of the prior work done on data provenance collection are outlined below:

3.1.1 Provenance Aware Storage System(PASS)

MuniswamyReddy et al [28] developed a provenance collection system that tracks system-level provenance of the Linux file system. Provenance information is stored in the same location as the file system for easy accessibility, backup, restoration, and data management. Provenance information is collected and stored in the kernel space. PASS is composed of 3 major components: provenance collector, and provenance storage, provenance query. The collector keeps track of system level provenance. It intercepts system calls which are translated into provenance data and initially stored in memory as inode cache. Provenance data is then transferred to a file system in an kernel database, BerkleyDB. This database maps key value pairs for provenance data for fast index look up. PASS collects and stores provenance information containing a reference to the executable that created the provenance data, input files, a description of hardware in which provenance data is produced, OS information, process environment, process parameters, and other/data such as a random number generator seed. PASS detects and eliminates cycles that might occur in provenance dependencies as a result of version avoidance. Cycles violates the dependency relationships between entities. For example, a child node could depend on a parent node and also be an ancestor of a parent node. PASS eliminates cycles by merging processes that might have led to the cycles. It also provides functionality for querying provenance data in the database. The query tool is built on top of BerkleyDB. For querying provenance, users can process queries using the provenance explorer. Query is done using commands such as MAKEFILE GENERATION which creates the sequence of events that led to the final state of a file or process. DUMP ALL, gets the provenance of the requested file.

3.1.2 HiFi

Bates et al. [31] developed system level provenance collection framework for the Linux kernel using Linux Provenance Modules(LPM), this framework tracks system level provenance such as interprocess communication, networking, and kernel activities. This is achieved by mediating access to kernel objects. Linux Security Model is a framework that was designed for providing custom access control into the Linux kernel. It consists of a set of hooks which is executed before access decision is made. LSM was designed to avoid problem created by direct system call interception. The provenance information collected from the kernel space is securely transmitted to the provenance recorder in the user space.

HiFi contains three components, provenance collector, provenance log and provenance handler. The collector and log are contained in the kernel space while the handler is contained in the user space. The log is a storage medium which transmits the provenance data to the user space. The collector contains the LSM which resides the kernel space. The collector records provenance data and writes it to the provenance log. The handler intercepts the provenance record from the log. This approach to collecting provenance data differs from our work since we focus on embedded systems and are concerned with input and output (I/O) data, which primarily involve sensor and actuator readings.

3.1.3 RecProv

RecProv [22] is a provenance system which records user-level provenance, avoiding the overhead incurred by kernel level provenance recording. It does not require changes to the kernel like most provenance monitoring systems. It uses mozilla rr to perform deterministic record and replay by monitoring system calls and non deterministic input. Mozilla rr is a debugging tool for linux browser. It is developed for the deterministic recording and replaying of the firefox browser in linux. Recprov uses PTRACE_PEEKDATA from PTRACE to access the derefrenced address of the traced process from the registers. It also ensure the integrity of provenance data up till the point at which a host is compromised by trace isolation. Mozilla rr relies on PTRACE which intercepts system calls during context switching. It uses PTRACE to monitor the CPU state during and after a system call. It uses PTRACE_PEEKDATA from PTRACE to access the derefrenced address of the traced process from the registers. System calls such as execve, clone, fork, open, read, write, clode, dup, mmap, socket, connect, accept are monitored which are used for file versioning. The provenance information generated is converted into PROV-JSON, a W3C standard for relaying provenance and also stored provenance data in Neo4j a graph database for visualization and storage of provenance graphs.

3.1.4 StoryBook

Spillance et al [34] developed a user space provenance collection system, Storybook, which allows for the collection of provenance data from the user space thereby reducing performance overhead. This system takes a modular approach; It allows the use of application specific extensions allowing additions such as database provenance, system provenance, and web and email servers. It achieves provenance capture by using FUSE for system level provenance and MySQL for database level provenance capture. StoryBook allows developers to implement provenance inspectors these are custom provenance models which captures the provenance of specific applications which are often modified by different application(e.g web servers, databases). When an operation is performed on a data object, the appropriate provenance model is triggered and provenance data for that data object is captured. StoryBook stores provenance information such as open, close, read or write, application specific provenance, causality relationship between entities contained in the provenance system. Provenance data is stored in key value pairs using Fable as the storage backend. Storybook allows for provenance query. It achieves this by looking up an inode in the ino hashtable.

3.1.5 Trustworthy whole system provenance for Linux kernel

Bates et al [8] provide a security model for provenance collection in the linux kernel. This is achieved by creating a Linux Provenance Model(LPM). LPM serves as a security layer which provides a security abstraction for provenance data. It is involved in the attestation disclosure of the application layer and authentication channel for the network layer. The goal of LPM is to provide an end to end provenance capture system. LPM ensures the following security guarantees: For LPM,the system must be able to detect and avoid malicious forgery of provenance data. The system must be trusted and easily verifiable.

When an application invokes a system call, the LPM tracks system level provenance which is transmitted to the provenance module via a buffer . The provenance module registers contains hooks which records system call events. These events are sent to a provenance recorder in the user space. The provenance recorder ensures that the provenance data is stored in the appropriate backend of choice. Provence recorders offer storage support for Gzip, PostGreSQL, Neo4j and SNAP.

3.1.6 Towards Automated Collection of Application-Level Data Provenance

Tariq et [36] all developed a provenance collection system which automatically collects interprocess provenance of applications source code at run time. This takes a different approach from system level provenance capture. It achieves provenance capture by using LLVM compiler framework and SPADE provenance management system. LLVM is a framework that allows dynamic compilation techniques of applications written in C, C++, Objective-C, and Java. Provenance is inserted during compilation. LLVM contains an LLVM reporter. This is a java class that parses the output file collected from the LLVM tracer and forwards the provenance data collected to the SPADE Tracer. SPADE is a provenance management tool that allows for the transformation of domain specific activity into provenance data. The LLVM Tracer module tracks provenance at the exit and entry of each function. The output is an Open Provenance Model in which functions are represented by an OPM process, arguments and return values are represented as an OPM artifact. To minimize provenance record, users are allowed to specify what functions they would like to collect provenance information at run time. The LLVM optimizer generates a graph of the target application. This graph is used to perform reverse reachability analysis from the functions contained in the graph. A workflow of how the framework works in collecting provenance is as follows:

- The application is compiled and converted into bitcode using the LLVM C compiler, clang.
- The LLVM Tracer module is compiled with bitcode.
- Provenance instrumentation is added to the bitcode via the LLVM Trace module.
- Instrumentation bitcode is converted into assembly code via the compiler llc
- LLVM Tacer and Reporter is compiled into assembly code.

- The instrumented application and assembly code is compiled into an executable binary and sent to the SPADE kernel.

One major limitation to this approach of collecting application level provenance is that a user is required to have the source code of the specific application in which provenance data is required. Also, provenance collection is limited to function's exit and entry points.

3.1.7 Provenance from Log Files: a BigData Problem

Goshal et al [16] developed a framework for collecting provenance data from log files. They argue that log data contains vital information about a system and can be an important source of provenance information. Provenance is categorized based on two types: Process provenance and data provenance. Process provenance involves collecting provenance information of the process in which provenance is captured. Data provenance on the other hand describes the history of data involved in the execution of a process. Provenance is collected by using a rule based approach which consists of a set of rules defined in XML. The framework consists of three major components. The Rule engine which contains XML specifications for selecting, linking and remapping provenance objects from log files. The rule engine processes raw log files to structured Provence. There are three categories of rules as specified by the grammar. The match-set rules which selects provenance data based on a set of matching rules. Link Rules which specifies relationship between provenance events and Remap rules are used to specifying an alias for a provenance object. This component is integrated with the log processor. The Log processor component is involved with parsing log files with information contained in the rule engine. It converts every matching log information to a provenance graph representing entities(vertices) and their relationship(edges). The adapter converts the structured provenance generated by the Log processor into serialized XML format which is compatible with karma, a provenance service application that is employed for the storage and querying of the provenance data collected.

3.1.8 Towards a Universal Data Provenance Framework using Dynamic Instrumentation

Gessiou et al [15] propose a dynamic instrumentation framework for data provenance collection that is universal and does not incur the overhead of kernel or source code modifications. This is achieved by using DTrace, a dynamic instumentation utility that allows for the instrumentation of user-level and kernel-level code and with no overhead cost when disabled. It allows to be included at every point in time in a system runtime without overhead issues from disabled probes.

The goal is to provide an easy extension to add provenance collection on any application regardless of its size or complexity. Provenance collection is implemented on the file system using PASS, on a database(SQLite) and a web browser(Safari). The logging component monitors all system calls for processes involved. The logging component contains information such as system-call arguments, return value, user id, process name, timestamp. The logging components includes functionalities to collect library and functional calls. The authors argue that applying data provenance to different layers of the software stack can provide varying levels of information. Provenance needs to be captured at the layer in which it is closest to the information that is needed to be captured. Provenance information that pertains to complex system activities such as a web browser or a database are collected. The information is collected from a process system-call and functional-call based on valid entry points contained in the process. DTrace dynamic instrumentation helps in discovering interesting paths in a system in which data propagates. This helps users use this information to collect a more accurate provenance data.

3.1.9 Provenance-based trustworthiness assessment in sensor networks

Lim et al. [25] developed a model for calculating the trust of nodes contained in a sensor network by using data provenance and data similarity as deciding factors to calculate trust. The value of provenance signifies that the more similar a data value is, the higher the trust score. Also, the more the provenance of similar values differ, the higher their trust score. The trust score of a system is affected by the trust score of the sensor that forwards data to the system. Provenance is determined by the path in which data travels through the sensor network. This work differs from our approach since the authors focus on creating a trust score of nodes connected in a sensor network using data provenance and do not emphasize how the provenance data is collected. We are focused on creating a provenance aware system for I/O operations which is used to ensure trust of connected devices.

3.1.10 Backtracking Intrusions

Samuel et al [24] developed a system, Backtracker, which generates an information flow of OS objects(e.g file, process) and events(e.g system call) in a computer system. From a detection point, information can be traced to pinpoint where a malicious attack occurred. The information flow represents a dependency graph which outlines the relationship between system events. Detection point is a point in which an intrusion was discovered. Time is included in the dependency between objects to reduce false dependencies. Time is denoted by an increasing counter. The time is recorded as the difference of when a system call is invoked till when it ends. Backtracker is composed of two major components: EventLogger and GraphGen. An EventLogger is responsible for generating system level event log for applications running on the system. EventLogger is implemented in two ways: using a virtual machine and also as a stand alone system. In a virtual machine, the application and OS is run within a virtual machine. The OS running inside of the virtual machine is known as the guest OS while the OS on the virtual machine is known as the host OS. The virtual machine alerts the EventLogger in the event that an application makes a system call and also when an application exits. EventLogger gets event information, object identities, dependency relationship between events from the virtual machine's monitor and also the virtual machine's physical memory. EventLogger stores the collected information as a compressed file. EventLogger can also be implemented as a stand alone system which is incorporated in an operating system. Virtual machine is preferred to a standalone system because of the use of virtual machine allows ReVirt to be leveraged. ReVirt enables the repay of instruction by instruction execution of virtual machines. This allows for whole information capture of workloads. After the information has been captured by the EventLogger, GraphGen is used to produce visualizations that outlines the dependencies between event and objects contained in the system. GraphGen also allows for pruning of data after it has been collected by the EventLogger. It contains regular expressions which are used to filter the dependency graph and prioritize important portions of the dependency graph.

3.1.11 Provenance Recording for Services

Grouth et al [18] developed a provenance collection system, PReServ which allows software developers to integrate provenance recording into their applications. They introduce P-assertion recording protocol as a way of monitoring process documentation for Service Oriented Architecture(SOA) in the standard for grid systems. PreServ is the implementation of P-assertion recording protocol (PreP). PreP specifies how provenance can be recorded. PreServ contains a provenance store web service for recording and querying of p-assertions. P-assertions are provenance data generated by actors about the execution. It contains information about the messages sent and received as well as state of the message. PreServ is composed of three layers, the Message translator which is involved with converting all messages receive via HTTP request to XML format for the provenance store layer. It also determines which plug-in handle to route incoming request, the Plug-Ins layer receives messages from the Message translator. It implements functionality that the Provenance Store component provides. This component allows third party developers to add new functionality to store provenance data without going through details of the code implementation. The backend component stores the P-assertions. Various backend implementations could be attached to the system by the plug-in component

3.2 Related Work on Policy-based provenance data storage

3.2.1 Take Only What You Need: Leveraging Mandatory Access Control Policy to Reduce Provenance Storage Costs

Bates et al [7] developed a system which allows maximizing provenance storage collection in the Linux OS environment using mandatory access control policy. this enables provenance avoidance of recording unnecessary provenance data and only recording interesting provenance that is important to an application. In MAC system, every object contains a label and the MAC policy specify interactions between different labels contained in the MAC. Provenance policy contains security context which is enforced by the MAC policy which contains permissions based on security context. IT provides the link between provenance and MAC. They argue that the system collects complete provenance without gaps in provenance relationship and still maintaining the MAC policy authorization domain. This is achieved by extending the work of Vijayakumar et. al.s [37] Integrity Walls project which allows mining SELinux policieswith the aim of finding Minimal Trusted Computing Base (MTCB) of various applications. A policy document is divided into trusted and untrusted labels. The trusted labels provides a thorough description of events relationship that can have access to the application. This information serves as a provenance policy that ensures a complete provenance relationship.

3.2.2 A Provenance-aware policy language (cProvl) and a data traceability model (cProv) for the Cloud

Ali et al [5] provides a provenance model, cProv, which illustrates relationships between entities contained in a cloud system. This model is build on PROV notation. cProv contains 5 derived nodes(cprov:cProcess, cprov:Resource, cProv:Transition, cprov:cResource, and cprov:pResource). There are a total of 10 edges built on the relationships contained in the PROV notation. Node consists of properties such as location, time-to-live, virtual-to physical mappings, executed operations. They also develop a policy language, cProvl that allows for access of provenance data. cProvl is represented in XML and consists of rules and conditions that expresses logic to enforce access of resources. Each rule contains an entity. XACML, a policy language for the enforcement of access control is used for implementing access control on the provenance policy information. cProvl is mapped to XACML to allow the policy to run on XACML which is widely used in the industry for access control implementation. An example of how the policy structure works is as follows: An application makes a request, this request is converted to the appropriate provenance aware request. This request is forwarded to the policy engine. The request is then evaluated by this layer by evaluating one or more policy rules as contained in a policy. This creates a response which is forwarded to the provenance converter which converted to the appropriate format for client utilization.

3.3 Related Work on Data Compression

3.3.1 Secure Data Provenance Compression Using Arithmetic Coding in Wireless Sensor Networks(WSN)

The authors [21] encode the provenance of the path in which a sensor provenance travels using arithmetic coding, a data compression algorithm. Arithmetic coding assigns intervals to a string of characters by cumulative probabilities of each character contained in the string. It assign probabilities by monitoring the activities of the WSN, this is known as the training phase. In this phase the number of times a node appears in a packet is counted. Each node in the WSN is regarded as a symbol. This is used as input to the arithmetic coding algorithm which generates a variable interval for the combination of symbols. For their application, provenance is referred to as the path in which data travels to the BS. The WSN contains a Base Station(BS) and a network of nodes. The base station is in charge of verifying the integrity of the packets sent. It is also where the encoded characters using arithmetic coding are decoded. According to the authors, provenance is divided into two types: Simple provenance in which data generated from the leaf nodes and are forwarded to surrounding nodes towards the Base Station. In the other form of provenance, data is aggregated at an aggregation node and forwarded to a BS. Each node in the WSN is represented as a string of characters and is encoded using arithmetic coding. The BS is responsible for decoding encoded provenance information. Provenance is encoded at the respective nodes and forwarded to the next node in the sensor network. The BS recovers characters the same way they were encoded. It also receives the encoded interval to which it uses to decode characters by using the probability values saved in its storage.

Chapter 4

Sensor Data Provenance Collection Framework for the IoT

In this chapter, we define how provenance is collected and modeled along the IoT architectural stack. We also define implementation specifics of our provenance collection framework.

4.1 IoT Provenance-Collection framework Information flow

A provenance model is used to represent causal dependency between objects and it is usually modeled as a Directed Acyclic Graph(DAG). This enables better graphical representation of provenance relationships and also a unified format for representing provenance data. There are two major models for representing provenance, OPM and Prov-DM. PROV-DM is a predecessor and standardized version of OPM. It allows the modeling of data objects either physical or digital. PROV-DM is chosen as the model to represent provenance for our implementation because it allows for the proper representation of all of the relationships in which we envision for IoT devices. This section defines a model for relaying provenance in IoT systems which is built on top of PROV-DM. From the IoT architecture as illustrated in Section 2, data is disseminated from sensors and actuators across various layers contained in the IoT architectural stack. The provenance data produced from various sensors and actuators are collectively aggregated at the gateway layer and/or the cloud layer. We allow provenance data to be translated to PROV-DM format at the various levels of the IoT architecture. This allows offline processing of information at all layers of the IoT architecture even in the case of a network failure. Figure 4.1 illustrates the provenance data aggregation that occurs at various layers of the IoT architectural stack. Data is collected from sensors and actuators and is collectively aggregated and passed across the various hierarchies contained in an IoT architecture.

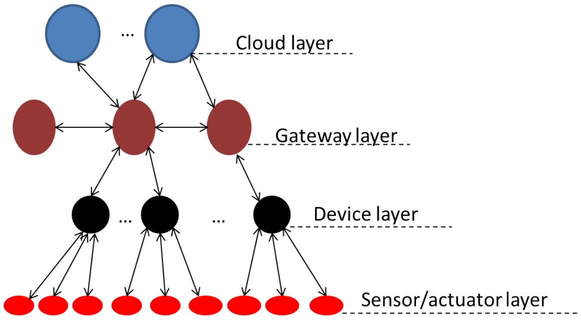


Figure 4.1: IoT provenance-collection data aggregation

Using the scenario of a smart home use case as illustrated in chapter 2, a detailed example of how our provenance collection framework can be applied is described as follows:

- Provenance data is collected from sensor and actuator readings of devices contained in the smart home(e.g thermostat, refrigerator, and smart doors). The provenance data is collected as specified in a policy document. Policy document contains information of which provenance data to be collected in the device and can be only be defined by the device owner who serves as an administrator.

- Provenance data from multiple sensor and actuator readings collected from each device is aggregated and passed along to the gateway. This information is transmitted to the cloud for storage in which further analysis could be conducted on the data to derive insights from the provenance data collected. This information is then transferred to the cloud for long term storage. Each layer in the provenance IoT architecture is independent of the and maintains provenance information that can be mapped using the PROVDM format which allows for the representation of dependencies that exists between objects contained in the device. This allows for provenance data to be further analyzed offline at the respective layers even in an event of network loss.

4.1.1 Provenance-Collection Model Definition

It is assumed that provenance data is collected from the underlying IoT device using the framework outlined in section 3 of this chapter. Data is collected from sensors and actuators attached to an IoT device. The underlying construct is represented as a acyclic graph which denotes the relationship between multiple sensors and actuator readings. Since PROV-DM type provides a generic model for relaying provenance information, we define a more specific construct for representing provenance data in IoT devices based on PROV-DM. In the context of IoT provenance, entity, process and agent are defined as follows:

- Agent: An agent contains information on an object that accesses an entity. Examples of agents in an IoT architecture are sensors, actuators, user roles(e.g admin). A unique identifier is given to each agents contained in an IoT framework.
- Entity: An entity can be defined as a data object that contains information which can be modifiable. An example entities are device files, processes, device memory contents.
- Activity: An activity is a modification that an agent makes on an entity. An example of an activity are basic file access operations such as read, write, delete, update.

To better emphasize the provenance-collection model, an example of a use case is illustrated in the figure 4.2 .

The figure 4.2 depicts a dependency relationship between two sensors, s1 and s2. Consider the scenario of a smart home. s1 is smart thermostat contained in a smart home which regulates the temperature of the home and s2 is a sensor that detects the outside

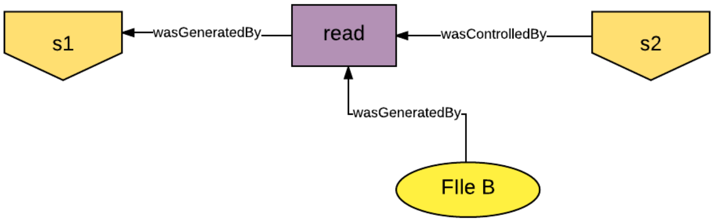


Figure 4.2: Provenance-model use case

temperature. s1 constantly checks the temperature outside to regulate the temperature of the house accordingly. s1 tries to access information from s2. According to the provenance data model definition, s1 and s2 are agents. The activity performed on s2 by s1 is read. File B is an entity in which s1 tries to read from s2 to determine the environmental temperature. The relationship between various components contained in the model is illustrated on the edges of the graph.

The relations define the relationship between types of a provenance model. We use the same instance of the relations contained in PROV-DM to represent relationships between types contained in the IoT framework.

4.2 Provenance-Collection System

In this section, we outline the components of our system and describe how provenance trace is collected across the IoT framework. Figure 4.3 displays the system architecture of our approach. Sensor and actuator readings in the form of Input and output(I/O) trace are recorded by the tracer component. This component intercepts system level I/O events and produces trace information in Common Trace Format (CTF). CTF represents binary trace output information containing multiple streams of binary events such as I/O activity. Trace information is converted into the PROV-DM and serialized to PROV-JSON. This represents the relationship between provenance entities contained in the system. CTF conversion to PROV-DM will be achieved using babeltrace. Babeltrace is a plugin which allows the conversion of CTF trace into various readable format. It includes plugins in which CTF trace data can be intercepted to create a custom conversion format. Trace data is securely transmitted to a gateway and later transmitted and stored in a private cloud backend. The backend of choice is Neo4j, a graph database for efficient storage, query and visualization of provenance data.

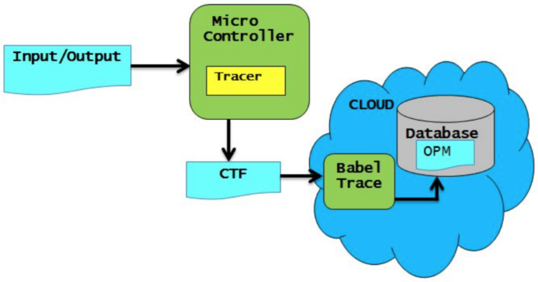


Figure 4.3: Proposed Model

The goal is to create a provenanceaware system which records I/O operations on data for devices connected in an IoT system. For our implementation, several tools and hardware components are utilized in the development of our prototype, some of the tools utilized are outlined below:

- BeagleBone Black Board. This device is a microcontroller used to evaluate our approach. We choose the BeagleBone Board because it is a representation of what can be found on an IoT gateway device and it has the capability to include custom hardware in programmable logic. Also, BeagleBone is a low cost, simple IoT demonstrator that was chosen for its high performance, onboard emulation, and IoT gateway projects can be programmed without additional need for hardware tools.

- Neo4j, a graph database which allow optimized querying of graph data. Since provenance represents causal dependencies, it is ideal to use a graph database to store the relationships between objects

- lttng, a software tool for collecting system level trace on Linux system.

4.3 Experiment Evaluation

I plan to evaluate the effectiveness of my approach for provenance collection by using an intrusion detection system specifically developed for IoT. An IDS is used to detect malicious attacks based on certain policy or threshold specified by an administrator. There are two types of IDS: rule-based/Signature-based approach, and anomaly-based approach. Signature-based approach allows for intrusion monitoring by specific known signatures of malicious attacks. An example of a signature-based IDS is an anti-virus software. On the other hand, anomaly-based IDS monitors intrusion by patterns that falls out of the normal system function. Most anomaly-based approach deals with the use of machine learning to classify normal or anomalous behavior. This can be useful to detect unknown malicious attacks. Provenance collection IDS system uses provenance data to provide intrusion detection capabilities in an IoT framework. It follows a Signature-based approach in which provenance data collected from the IoT framework is used for intrusion detection.

The IDS is developed using the work of Xie et al [38]. Xie et al proposed an intrusion detection system, Provenance-aware Intrusion Detection and Analysis System(PIDAS). This system uses system-level provenance data to provide real-time vulnerability intrusion detection on system behaviors. The system collects provenance from system calls, detects intrusion and analyzes vulnerabilities that exists based on provenance data. PIDAS contains three essential components: the collector which records provenance information of applications running in the user space. Provenance data is stored in a key-value pair database for easy query of acyclic graphs. The detector extracts dependency relationships from the provenance data and stores this information in a repository for further analysis. The analyzer is responsible for identifying all other intrusion activities that might have occurred. It achieves this by making queries to view all dependencies from the detected intrusion point. Provenance detector is made possible by using a provenance-based algorithm that matches the path contained in the graph.

The detector consists of three steps. Rule-buit which collects normal system behavior of provenance data and stores this information in a ruleDB. A ruleDB consists of a key-value pair which has parent and child relationships in the dependency graph. The rule-built is used to match observed provenance events to detect system intrusion. Provenance information in the form of a dependency relationship is matched with the child/parent dependency rule information contained in the ruleDB. This information is used to compute the decision value which determines if there has been an intrusion. A description of the rule matching and scoring algorithm is described in detail below:

- provenance data is divided into dependency relationships, $Dep_1, ..., Dep_n.Dep_i = (A, B)$. Where A is the parent of B

- The algorithm checks if there exists a match in the path between edges contained in the provenance dependency database, ruleDB. If there exists a path, a score of 1 is given to the path. This score is known as the path dubiety. Otherwise, if the path does not match any edge in the ruleDB, a score of 0 is given to the path.

  Let R = provenance information of a program and G = provenance information contained in ruleDB. For each $Dep_i = (A, B) \in R, if Dep_i = (A, B) \in G.$ intrusion dubiety = 1 else set intrusion dubiety = 0

- The path decision, P is the sum of the dubiety of all the edges contained in the provenance data divided by the number of paths contained in the provenance dependency database.

$$P = \frac{\sum_{i=1}^{W} dubeityofDep_i}{W}$$

  This information is compared with a threshold value, T. If P > T, an anomaly exists in the system.

I plan to compare the evaluation of our proposed framework using PIDAS with a baseline which consists of an implementation of PIDAS on an embedded system.. More specifically, I plan to evaluate the false negative and false positive rate for the IDS system as compared with the baseline. False positive dictates the number of times in which an intrusion has been wrongly detected. This signifies that a path contained in an applications provenance was detected and not found in the ruleDB. On the other hand, false negative rate identifies the number of times a intrusion has not been detected. I also plan to evaluate the throughput of the system by evaluating the overhead incurred using the .

Chapter 5

Storage Optimization Framework for Provenance Data Storage in IoT devices

In this chapter, we define our model and algorithms for storage optimization of provenance data in IoT. We focus on our proposed data pruning technique. We evaluate our hypothesis using the proof of concept ideology.

5.1 A policy-based approach to efficient provenance storage

Provenance generates more data than the data in which provenance is being collected. Due to the large influx of real-time data generated from sensor and actuators in IoT, we envision large amounts of provenance data will generated from our provenance collection framework. The resource constraints on the sensor/actuator and the device layer of the IoT architecture makes it even more challenging. There is a need to create an efficient storage framework for storing provenance data. To address this issue, we define a policy driven framework that provides a policy scheme for the enforcement of provenance storage. Policy approach allows the flexibility of provenance selection. A policy approach makes selecting what provenance is considered important to a specific IoT architecture thereby eliminating irrelevant provenance information. Since various organizations have varied provenance requirement(s), making provenance static might not be suitable across all IoT architecture. The approach of using policy for enforcement is slightly different from the typical access control approach. In other words, Policy is used for the resource enforcement of provenance data collected. This enables efficient pruning of provenance data in which all irrelevant data discarded. The policy framework consists of a policy document. This document contains information on provenance data that is considered relevant to the IoT architecture. A policy framework is used to address resource constraints encountered when storing large amounts of provenance data on low memory devices. Policy document is created by a user who serves as an administrator. An administrator is a user which has the right to add, delete or modify a policy document. For implementation, there are several policy models that can be utilized to integrate a policy model with the IoT framework.

Our policy architecture is modeled using the Common Open Policy Service(COPS) Standard [20]. COPS consists of components for policy generation, evaluation and enforcement. The Policy Enforcement Point (PEP) enforces decisions received from the Policy Decision Point (PDP). The PDP evaluates policies and generates decision based on the evaluation. The model is extended to include a secondary decision point(SDP). This allows for distributed policy evaluation, freeing up the PDP from communication bottlenecks caused by large amounts of request received by a single PDP. The figure below illustrates the system architecture of our proposed framework. Various layers of the IoT architecture contains different components of the decision and enforcement model. The Sensor/actuator layer of the IoT architecture is omitted. This is due tot he fact that this layer has the largest amount of memory restraints. Additionally, sensors and actuators are contained in the device layer and and as such does not require that data be pruned at this layer.

Policy document is generated at the device layer and evaluated at the gateway and cloud layer. The PEP which is involved with generating requests is located in the device and gateway layer. SDP is located in the gateway layer. This allows for policy evaluation without inuring additional network overhead of communicating with the PDP located in the cloud layer. To implement our policy based framework, We propose to use the eXtensible

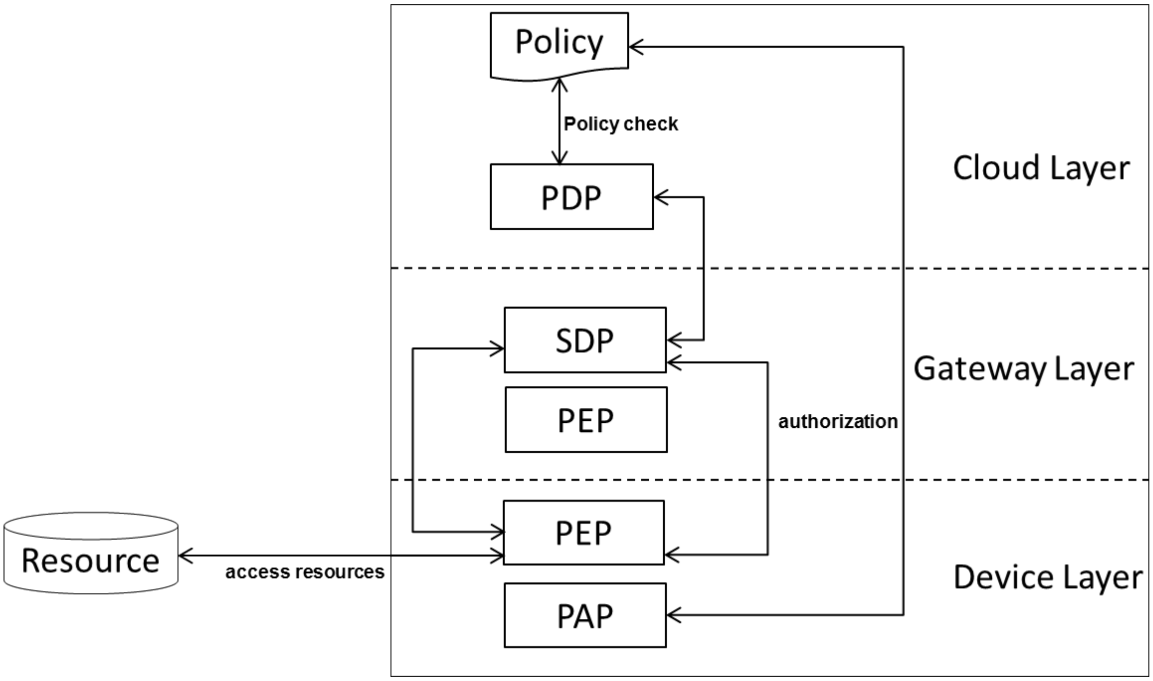


Figure 5.1: Policy based system architecture which allows for effective data storage of provenance data

Markup Language(XACML) policy model [1] to generate and enforce provenance policy for our IoT framework. We extend XACML to include the SDP component.

5.1.1 eXtensible Access Control Markup Language

XACML is an access control policy language that allows the creation and enforcement of policies written in XML. It is a standard specification developed by the Organization of Advancement of Structured Information Standards(OASIS). Since it is written in XML, this framework allows for extensible and flexible policy documents. XACML consists of three major components which are involved in policy generation, evaluation and enforcement. The components of XACML are described below:

- Policy Administration Point (PAP): This component of XACML is involved with the generation of policy documents. A Policy document is created by specifications and requirements set aside by an administrator.

- Policy Decision Point (PDP): The Policy Decision Point evaluates policies by the request context generated by a user. Based on the request, It generates a response(accept,deny or intermediate) This response is communicated with the Policy Enforcement Point which enforces the response sent by the PDP.
- Policy Enforcement Point (PEP): The Policy Enforcement Point generates request context which is sent to the PDP for evaluation. It is also involved with the responsibility of enforcing request based on decision received by the PDP.

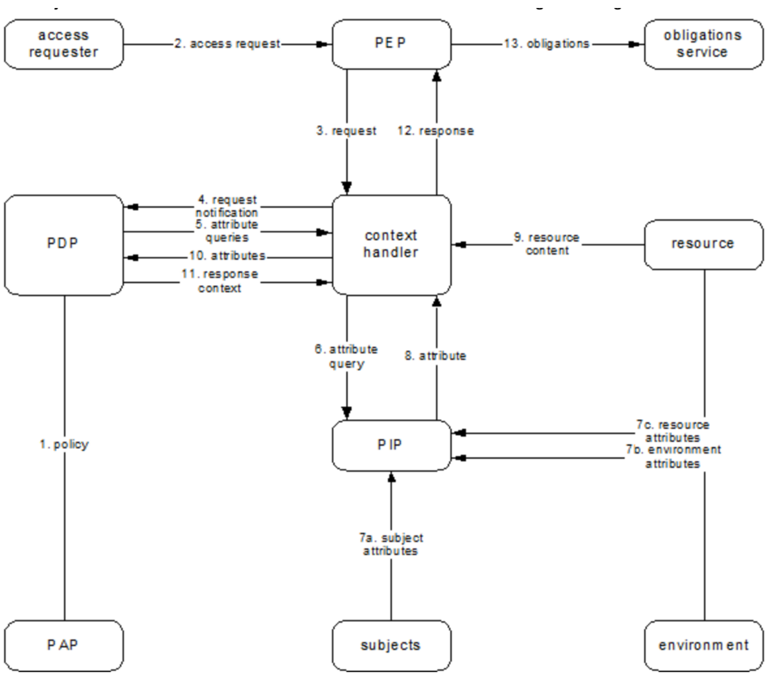


Figure 5.2: Xacml Data-flow diagram

Using the use case of the smart home depicted in chapter 2, a policy framework could be implemented and incorporated into the IoT which allows a device administrators to specify what kinds of provenance data to collect. The policy acts an enforcement point providing an efficient storage mechanism in a resource constrained environment. The contents of the implementation details for the policy framework which specifies the policy grammar and the policy architecture across the IoT stack are left as future work.

5.2 Provenance-model Information Flow

This section defines the unification of various components of IoT provenance collection system. Figure 5.3 depicts a flowchart that shows how provenance data is generated and how access control is enforced for provenance data. Input documents are represented in green while processes are represented by the blue rectangles. The document of various components contained are needed as input parameters to the processes that makes up the architecture. Policy document is generated by the administrator who decides what kinds of provenance data to collect. The administrator can be a device owner who has access and authority to the device. A policy framework is passed as an input to the the yaml generator component. This component is in charge of generating yaml files which specifies what CTF trace to collect in the application. The yaml configuration is a essential portion of the provenance collection system. It is used to generate application later trace. It contains instructions of what trace data to collect.

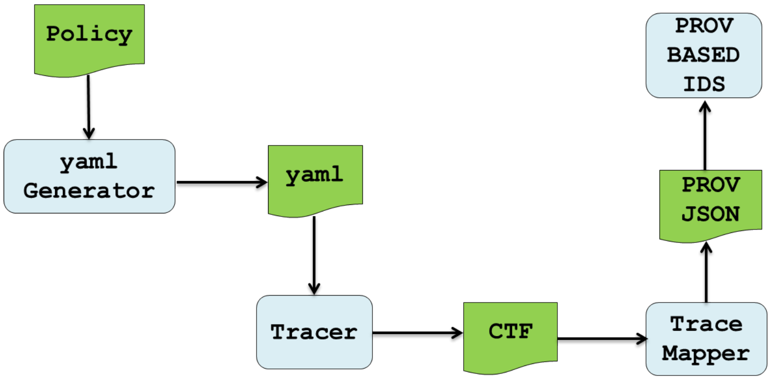


Figure 5.3: Architectural Flowchart

Chapter 6

Conclusion

6.1 Summary

In this research, we motivate the need for integrating provenance into the IoT architecture. We propose a provenance collection system that provides provenance collection capabilities for devices contained in an IoT framework . Provenance data is believed to be beneficial in mitigating current and future malicious attacks. To address the issue of provenance storage, we also propose a framework for efficient provenance data storage.

6.2 Future Work

Some of the proposed future work for this research is outlined bellow:

- Provenance collection raises privacy issues. How do we ensure that the vast amount of data collected is not invasive to the privacy it is not used as a tool to perform malicious attacks.

- Provenance Query: How do we query provenance data in order to interpret provenance information and make analysis of data collected.

- Provenance Versioning: Provenance version creates cycles. When a file is read or edited, is a new instance of the file created? Tracking all transformations that occurs on a data object in memory constrained devices might lead to running out of storage space.

- Securing Provenance: Due to the great level of sensitivity that provenance data entails, it is of utmost importance to ensure the confidentiality and integrity of provenance data stored on IoT devices while at rest or in transit. Proper encryption and authentication techniques [19] is need to ensure the confidentiality, integrity, and availability of provenance data.

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