A Unified Knowledge Representation and Context-aware Recommender System in Internet of Things

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Abstract. Within the rapidly developing Internet of Things (IoT), numerous and diverse physical devices, Edge devices, Cloud infrastructure, and their quality of service requirements (QoS), need to be represented within a unified specification in order to enable rapid IoT application development, monitoring, and dynamic reconfiguration. But heterogeneities among different configuration knowledge representation models pose limitations for acquisition, discovery and curation of configuration knowledge for coordinated IoT applications. This paper proposes a unified data model to represent IoT resource configuration knowledge artifacts. It also proposes IoT-CANE (Context-Aware recommendation system) to facilitate incremental knowledge acquisition and declarative context driven knowledge recommendation.

Keywords: Conceptual model · Recommender system · Internet of Things.

1 Introduction

The Internet of things (IoT) refers to the general idea of things that are readable, recognizable, locatable, addressable and controllable via the Internet [123]. In IoT, a notable aspect is abstraction of resources as services. This has laid the foundations for a plethora of applications such as smart home, smart building, smart office, smart transportation, smart cities, smart traffic, etc., where users can search, query and actuate entities in real-time. These services are provided by a huge number of heterogeneous objects that are directly related to the physical world. These objects are not only physical objects, such as physical sensors and actuators, but also virtual objects, like social media (Facebook, Twitter, etc.,). Thus, there is a need for seamless integration of the physical world with the
digital world in IoT. The data and services provided by these objects need to be defined in a homogeneous way to allow interoperability [4].

Consider a scenario of a fresh IoT application manager that would like to build a smart home application without a large amount of money. The manager may purchase IoT devices from multiple manufacturers with low price, such as temperature sensors, motion sensors, humidity sensors, Raspberry Pi etc. We assume this manager does not have enough knowledge of Cloud resource configuration and Edge resource configuration and deployment. Hence, the manager needs to find some solution provider to offer IoT resource configuration management and deployment solutions. However, the majority of IoT application solution providers that can offer different IoT application solutions to the user are expensive. Moreover, IoT application solution providers can only provide existing services within their service list with the IoT devices supported by their software. Besides, IoT devices produced by different manufacturers may have different API which increases the difficulty of service deployment from a single IoT application solution provider. From now on, there are 313 available APIs from ProgrammableWeb website [18]. In another case, this smart home manager purchases a new smart camera to enhance his smart home application with an intrusion detection service. He may need to connect this new smart camera to his smart home environment, for example, by building a connection between the camera and a gateway to collect graph data. The householder may have already implemented the smart home with the help of professionals. But it may not be affordable or practical to seek help every time he purchases new IoT devices.

In order to address the aforementioned problems, we present a high-level, simplified context-aware IoT resource configuration recommender system (IoT-CANE). We identify and formalize the knowledge of multiple configurations of Edge and Cloud infrastructure. The core idea in our IoT recommender system is to formally capture the knowledge of IoT resource configuration using a declarative language, and then implement it in a recommender service on top of a relational data model. Execution procedures in the IoT recommender are transactional and apply well-defined SQL semantics for querying, inserting and deleting IoT resource configurations. The contributions of this paper can be summarized as follows:

- A unified and formalized conceptual model capable of fully describing resource configurations in IoT. The model is based on, and has been successfully validated against the most commonly available infrastructure providers for both Edge and Cloud.
- An implementation of a design support recommender system for the recommendation of resource configuration in IoT using transactional SQL semantics, procedures and views. The benefits to users of the IoT recommender include, for example, better performance and cost saving from multiple IoT resource providers.
- A user-friendly service interface that maps user requirements based on simple form inputs to optimal IoT resource configurations, expresses configuration selection criteria, and views the results.
The remainder of the paper is organized as follows. Related work about resource configuration management issues in IoT and recommender systems is presented in Section 2. A detailed description of the conceptual model and system architecture is presented in Section 3. Evaluation of a use case study is provided in Section 4 before the conclusion and future work in Section 5.

2 Related Work

2.1 Multi-layer Resources Configuration Management Issues in IoT

The recent trend in composing Cloud applications is driven by connecting heterogeneous services deployed across multiple datacenters [5]. Such a distributed deployment aids in improving IoT application reliability and performance within Edge computing environments. Ensuring high levels of dependability for such IoT data transformation tasks composed by a multitude of systems is a considerable issue. Various Cloud resource description and deployment frameworks are proposed in industry and research. Market-leading Cloud resource providers such as AWS OpsWorks [15] and CA AppLogic [16] allow describing and deploying complete application stacks. These providers offer provider-specific resource representations. In Edge computing, Docker [17] provides deployment and configuration management solutions for Edge devices based on container techniques. However, there are not only Cloud and Edge in IoT resources configuration management, but also physical devices which are deployed widely in IoT applications. In IoT, all the resources from multi-layers need to be considered in a single application which leads to complicated scenarios.

2.2 Context-aware Recommender Systems

The concept of context has significantly evolved since it was first introduced in [6]. Nowadays, it is widely accepted that there may be diverse kinds of contextual information classified into three main categories: user context (e.g. location and mood), device context (e.g. network bandwidth and display resolution) and physical context (e.g. time and weather) depending on the perspective adopted: user-side or application-side. The interpretation of context may vary between one application and another according to the domain and architecture of the application so that it is quite suitable to give a definitive definition of this concept. For instance, [7] described possible interpretations of context across different fields concerned with recommender systems such as e-commerce and ubiquitous systems. Although location seems to be a recurrent kind of contextual information among context-aware recommender systems, it does not always refer to the geographical location of the user either relative or absolute as in the case of the social tag-based collaborative filtering approach proposed by [8] as part of a smart TV system. This approach is context-aware in the sense that it considers information about both user context and device context. Here, the recommendations are solely computed from user preferences, then the resulting recommendations are re-ranked accordingly. In [9], the authors presented a
framework to provide declarative context driven knowledge recommendations for federated Cloud resources configuration. In this framework, they give recommendation of configuration knowledge artifacts based on a given context. However, these frameworks provide context-driven recommendation in Cloud computing while in our approach, context-aware recommendations are given in the IoT area which is more complicated.

2.3 Knowledge-based Recommender System

A knowledge-based recommender system is one specified type of recommender system based on explicit knowledge about the item assortment, user preferences, and recommendation criteria. The use of a semantic description of the domain in which the recommendations are provided has become an increasingly common approach towards the improvement of the quality of the recommendations. To this aim, ontologies have been used as the preferred mechanism due to their capacity for semantically describing concepts without the constraints typically imposed by other models such as databases. In fact, ontologies are formal and explicit descriptions of shared conceptualizations, and they can be exploited in several ways. Recent proposals in recommender systems literature take advantage of ontologies to model the features of users besides the features of the items in the domain of the systems, i.e. the items handled by the systems [10]. This approach has resulted in so-called ontology-based user profile modeling. Furthermore, starting from ontology-based user profiles and domain ontologies, recommendation processes can in part be addressed as implicit knowledge inference processes. For instance, an ontology-based recommender system for tourism and leisure activities called SigTur/E-Destination was proposed in [11]. This system takes advantage of a domain ontology; this ontology also guides the recommendation process to some extent. In our approach, a knowledge base is built to store relevant resource configuration artifacts to provide further knowledge-based recommendations to new customers.

3 Conceptual Model and System Architecture

3.1 Conceptual Model

An IoT framework can benefit from structured models that detail various concepts and provide abstractions of the components and their attributes. This section defines the main abstractions and concepts that underlie the IoT and describes the relationships between them. One of the main concepts of our research work is the unified knowledge representation for IoT resource configurations. We describe a unified hierarchical representation model based on the entity-relationship modeling (ER model), shown in Fig1. [1] The physical resources part of our model is based on Semantic Sensor Network (SSN) Ontology [14]. In SSN ontology, sensors and observations, and related concepts, are described without domain concepts, time, locations, etc. Moreover, Edge and
Cloud resources are considered to improve the conceptual infrastructure model for IoT.

In Fig. 1, an IoT ‘service’ provides a well-defined and standardized interface, offering all necessary functionality for interacting with IoT resources and related processes. IoT resources consist of three main entities, physical resources, Edge resources and Cloud resources. Physical resource class describes the attributes of sensors and actuators in the conceptual model. Edge resource class and Cloud resource class describe the capability of compute, network and storage in the conceptual model. Each IoT service provides a well-defined and standardized interface, offering all necessary functionalities for interacting with resources and related processes. The services expose the functionality by accessing multiple resources. The identified concepts need to be modeled in a format that provides inter-operable and automated human and machine interpretable representations.

We will present a partial description of infrastructure components for a smart building scenario using the proposed conceptual model.

As shown in Table 1, the sensor class contains five attributes – sensorType, locationName, latitude, longitude and availability – to describe resource type, geographical area and running time availability respectively; the actuator class contains five attributes as well; the operating range class contains resolution, responseTime, measurementRange, precision, latency and accuracy attributes; in each line, we presented a short description to explain the meaning of attribute. Besides, we presented a simple instance based on the smart building scenario we proposed in the first section.

3.2 System Architecture

In this section, we will present the system architecture of IoT-CANE.

This rule based recommendation system is intended to automatically suggest configuration knowledge artifacts to multiple layers required for users during
Table 1. Partial infrastructure components description and instance of smart building in IoT data model

| Class | Attribute | Type   | Description                                                                 | Instance in Smart Building |
|-------|-----------|--------|-----------------------------------------------------------------------------|-----------------------------|
| resource | resourceName | String | Name of the resource                                                        | Smart temperature sensor    |
|        | resourceType | String | Resource type, such as physical, virtual, and cloud resources                | Physical resources          |
|        | accreditType | String | Interface type, such as REST, SOAP, and XML-RPC                              | RESTful API                 |
|        | hasTag     | String | Description of the resource                                                 | Intelligently measure the temperature of the specific area |
| actuator | actuatorType | Actuator type | Actuator type, such as physical(locker), virtual(social media), and smart physical | Smart temperature sensor    |
|        | locationName | String | Geographical area in which the actuator is located                          | Kurdistan                   |
|        | latitude    | Float  | Latitude of the actuator                                                     | 54.9783 N                   |
|        | longitude   | Float  | Longitude of the actuator                                                    | 1.6178 W                    |
|        | availability | Boolean | Actuator availability                                                       | available                   |
| sensor  | sensorType  | Sensor type | Sensor type, such as physical(temperature), virtual(social media), and smart physical | Smart temperature sensor    |
|        | locationName | String | Geographical area in which the sensor is located                            | Kurdistan                   |
|        | latitude    | Float  | Latitude of the sensor                                                       | 54.9783 N                   |
|        | longitude   | Float  | Longitude of the sensor                                                      | 1.6178 W                    |
|        | availability | Boolean | Sensor availability                                                         | available                   |
|        | resolution  | String | The smallest difference in the value of an observable property being observed that would result in perceptible different values of observation results | The smallest difference in the value of an observable property being observed that would result in perceptible different values of observation results |
|        | measurementRange | String | A set of values that the sensor can return as the result of an observation | -55 to 150°C                |
|        | precision   | String | As an actuator: the closeness of agreement between replicated actuations of an unchanged or similar command | ±0.36°C (max)              |
|        | latency     | String | The time between a command for an observation and the sensor providing a result | 500ms (max)                 |
|        | accuracy    | String | The closeness of agreement between the result of an observation (command of an actuation) and the true value of the observed | ±0.1°C                      |

Fig. 2. IoT-CANE architecture
IoT resource configuration management processes (such as IoT resource deployment and configuration parameter modification). Recommended suggestions are generated based on a user specified context (e.g. service category, data source and programming model). This context represents an individualized IoT data transformation task or an IoT service requirement. The suggested configuration knowledge includes all necessary information and instructions, required to deploy an Edge or a Cloud resource configuration, which satisfies the context description. This system derives suggestions from configuration knowledge artifacts, such as executable deployment scripts and packaged virtual appliances, that were created for similar contexts in the past. Users can accept or modify recommended configuration knowledge artifacts according to their requirements. Alternatively, users can reject the recommendation, and create a new configuration knowledge artifact from scratch. Once such modifications are completed, the recommender system translates those modification into recommendation rules with the help of users and makes available new recommendations for future user requests. Finally recommended knowledge artifacts are input into a Docker deployment interface to provision concrete configurations. Detailed processes among user, administrator and system are listed in Fig. 2.

We will introduce recommendation rules of the recommender system, followed by the construction origin and evolution of recommendation rules below.

**Recommendation Rules** This recommender system maintains an IoT resource configuration knowledge base (KB) which stores contexts, configuration knowledge representations and configuration knowledge artifacts, shown in Fig. 3. Recommendation rules maintain associations between those items in the KB as shown in the figure. Recommendations consist of contexts and conclusions.

![Fig. 3. Example of recommendation rule tree structure](image)

**Contexts** the left hand side of the UML diagram contains the context information. The recommender system maintains “contexts” data of the intended service category (e.g. temperature sensing, motion sensing), data source (e.g.,
Conclusions} the right hand side of the UML diagram depicts components which construct the conclusion of a recommendation rule. Recommendation rules suggest configuration knowledge representation. Users can deploy the configuration knowledge representation via a specific provider’s configuration deployment service, such as Docker. In some situations, users may need to submit knowledge representations to specific deployment services and generate knowledge artifacts, such as virtual appliances. For example, Docker API firstly generates an image from a submitted knowledge representation and next users should submit the image to Docker API for deploying concrete Edge or Cloud resources, such as containers. Users can manage the deployed resources configuration afterward.

**Single Conclusion Ripple Down Rules** To facilitate efficient reuse of existing configuration knowledge representations for modeling heterogeneous IoT resource configurations, we use a knowledge acquisition and maintenance method called ripple down rules (RDR) [12]. We decided to choose RDR as it empowers reusability of existing configuration knowledge representations and configuration knowledge artifacts. RDR also enriches knowledge by creating and integrating new rules to the existing knowledge base. The RDR technique has been successfully implemented in many domains (e.g. natural language processing, clinical pathology reports, call centers, database cleansing, UI artifact reuse and soccer simulations). But to the best of our knowledge, there has been no attempt to adapt RDR to the domain of IoT resources configuration knowledge reuse.

There are different variations of RDR such as single conclusion RDR, multiple conclusion RDR and collaboration RDR [13]. For evaluation purposes of our recommender system, we implemented a single conclusion RDR technique which allows only one conclusion for a given context.

The figure shows the tree structure of recommendation rules in the knowledge base. Rule A0 contains the default conclusion named “unknown”. The recommender system suggests the default conclusion when the input context is not specified. Thus, the inference engine triggers the default conclusion, when the service category, data source and other information are not defined in input contexts. The KB depicts “except” (true) branches and “if not” (false) branches. When users input a context to the recommender system, the inference engine starts querying the recommendation rule tree. Starting from the root node, the engine checks whether the next rule node is true or false by comparing the context of each rule node with the user specific context. This task is carried out repeatedly until the inference engine cannot proceed to find any more true
nodes. Then the conclusion of the last true node is returned back to the user. This is done for each aspect (i.e. service category, data source, programming model and deployment node).

\[
\text{Rule A0} \\
\text{IF } SC = (\text{undefined}) \land DS = (\text{undefined}) \land PM = (\text{undefined}) \land DN = (\text{undefined}) \text{ THEN KID } = \text{unknown}
\]

- SC = Service Category
- DS = Data Source
- PM = Programming Model
- DN = Deployment Node
- KID = Configuration Knowledge Representation ID

\[
\text{Rule A1} \\
\text{IF } SC = \text{"temperature sensing"} \land DS = \text{"physical sensor"} \land PM = \text{"SQL"} \land DN = \text{"Edge node"} \text{ THEN KID } = \text{"A001"}
\]

\[
\text{Rule A2} \\
\text{IF } SC = \text{"temperature controlling"} \land DS = \text{"temperature sensor"} \land PM = \text{"SQL"} \land DN = \text{"raspberry pi"} \text{ THEN KID } = \text{"B001"}
\]

\[
\text{Rule A3} \\
\text{IF } SC = \text{"motion sensing"} \land DS = \text{"physical sensor"} \land PM = \text{"NoSQL"} \land DN = \text{"Edge node"} \text{ THEN KID } = \text{"C001"}
\]

\[
\text{Rule A4} \\
\text{IF } SC = \text{"intrusion detection"} \land DS = \text{"motion sensor"} \land PM = \text{"NoSQL"} \land DN = \text{"gateway"} \text{ THEN KID } = \text{"D001"}
\]

\[
\text{Rule A5} \\
\text{IF } SC = \text{"event detection"} \land DS = \text{"social media"} \land PM = \text{"Streaming"} \land DN = \text{"Cloud node"} \text{ THEN KID } = \text{"E001"}
\]

\[
\text{Rule A6} \\
\text{IF } SC = \text{"event detection"} \land DS = \text{"twitter"} \land PM = \text{"Streaming"} \land DN = \text{"AWS EC2"} \text{ THEN KID } = \text{"F001"}
\]

\[\text{Fig. 4. Example of recommendation rule tree structure}\]

For example, a curator of our KB may want to model an IoT resource configuration for a temperature controlling application as an Edge deployment. But assume our KB does not contain this service category in any IoT application at this moment. That means Rule A2 does not exist in Fig. 4. The interface engine queries the KB and finds a configuration knowledge representation that is associated with service category “temperature sensing” and deployment node “Edge node” (Rule A1). But the curator cannot find an expect rule that originated from Rule A1. Therefore the curator firstly evaluates the configuration knowledge representation associated with Rule A1 and determines if that configuration knowledge representation is satisfactory for deploying a temperature controlling application. Unless the curator modifies the suggested configuration knowledge representation such that it describes the configuration with required component resources for the temperature controlling application environment, then the curator registers an expect rule (Rule A2) under Rule A1 and refers to the modified configuration knowledge representation as the conclusion of Rule A2.

In another scenario, an IoT resource user may need to deploy an intrusion detection on a gateway (Edge device). The inference engine checks in the rule
tree for a rule whose service category is equal to “intrusion detection” and deployment node is equal to “gateway”. The inference engine checks along the “if not” pathway in the rule tree and realizes that the last rule node that is set to true is Rule A4. Hence the conclusion of Rule A4 is recommended back to the user.

The knowledge base, empowered by SCRDR, incrementally acquires configuration knowledge in the form of rules. Any changes in service category, data source, programming model and deployment nodes activate an update to the KB. The following two cases create new Recommender Rules in our KB.

- A new configuration knowledge representation is registered on an existing service combination in the KB
- A configuration knowledge representation is registered or modified on a non-existing service combination in the KB

**Case 1** Users who expect to register a configuration knowledge representation model, can register rules by specifying an existing service category, data source and deployment node as the context and referring the new configuration knowledge representation model as the conclusion.

**Case 2** Administrator who needs to register or modify a configuration knowledge representation.

These processes allow the incremental evaluation of our SCRDR based knowledge base. Our approach makes more productive suggestions when there are enough rules. So our approach needs little user effort to specify contexts of rules when rules are being created.

In summary, our rule based recommender system lets users focus on their application and resource requirements while the system shields users from the technical complexity of multiple IoT resource configuration solutions.

### 3.3 System Logic

The request for resource configuration representation recommendation in IoT-CANE is expressed as SQL queries. Fig. 5 shows the recommendation logic in a simple diagram. Next we explain the basic steps which are executed for resolving a resource configuration representation recommendation request.

1) System combines user's input context information to a SQL query;
2) The above temporary SQL query will be executed in the recommendation rule database to produce a possible result;
3) Based on the result from rule database, map the result to configuration representation database with rule number and show in the user interface;
4) According to user satisfaction, new rule and configuration representation will be updated in respective database after administrator's operation.
Fig. 5. Recommender system processing diagram

Table 2. IoT recommender model parameters

| Notations | Meaning |
|-----------|---------|
| Query     | A configuration selection query |
| SC = \{sc_1,...,sc_n\} | Set of n service categories |
| DS = \{ds_1,...,ds_m\} | Set of m data sources |
| PM = \{pm_1,...,pm_o\} | Set of o programming models |
| DN = \{dn_1,...,dn_p\} | Set of p deployment nodes |
| N         | Number of rows in a relational database |
| M         | Number of column in a relational database |
3.4 Computational Complexity

In this section, we will discuss the computational complexity of our configuration selection logic. We give the detailed discussion of model parameters in Table 2. In the worst case scenario, the logic needs to compute a full cross join. The number of choices varies depending on the number of rows in each table. In the worst case scenario, the combination of the rules is a full CROSS JOIN over all existing rules. Therefore, the selection queries, to the best of our knowledge, have the upper bound computational complexity of equation (1):

\[ O_{\text{query}}( \sum_{i=1}^{sc_{\text{max}}} sc_i \times \sum_{i=1}^{ds_{\text{max}}} ds_i \times \sum_{i=1}^{pm_{\text{max}}} pm_i \times \sum_{i=1}^{dn_{\text{max}}} dn_i ) \]  

(1)

However, in a worst case the database system lacks support for cached views in a worst case the effort multiplies with the effort of the views’ JOIN. Modern databases can use HASH JOIN which has a computational complexity if O(N+M), and MERGE JOIN which has a computational complexity of O(N*Log(N)+M*Log(M)) which are faster than O(N*M).

4 User Evaluation

In this section, we present the experiments and evaluation that we undertook.

Experiment setup We hosted the IoT-CANE on a local machine with 64bit Mac OS X operating system. The machine has the following hardware configuration: Processor (2.4 GHz Intel Core i5); Memory (8GB 1600 MHz DDR3); Graphics (Intel Iris 1536 MB); Storage (256 GB SSD). We chose MySQL database to implement the knowledge database.

User Evaluation In order to evaluate the IoT-CANE, we performed a use case study to investigate the performance and acceptance of this system. Ten participants were invited to join the experiment. All participants are PhD students working in the Cloud Computing and Internet of Things area at Newcastle University. All of them had experience of deployment and configuration management in Cloud infrastructure and Edge devices. None of them had experience of using a recommender system for IoT resource configuration selection. The participants were asked to use the IoT-CANE under demonstration of administrator. They did a questionnaire after application testing. We gave nine questions to evaluate their experience and opinion of our IoT-CANE. Some of the results are shown in Fig. 6.

As shown in Fig. 6, most of the participants were satisfied with the IoT recommender system in the following ways: ease of use; reasonable recommendations; pleasant user interface etc. Based on their feedback, it can easily be concluded that the conceptual model covers the majority of resource configuration knowledge in IoT and the IoT-CANE can provide reasonable recommendations to IoT
application users. However, not all of the participants think so. The final question in the survey asked the participants to give some suggestions to improve our IoT recommender system. Their suggestions can be categorized as follows:

- They wanted new features, such as automatic deployment;
- They suggested that the user interface could be more descriptive and user friendly;
- They suggested that the IoT recommender system could provide multiple choices of the configurations which can handle more scenarios.

Based on their suggestions, our IoT recommender system needs to be improved in two ways: (1) to provide a new service which can convert JSON format configuration files into Docker-readable configuration files, such as YAML format; (2) to provide automatic deployment service based on container techniques.

5 Conclusion and Future Work

In this paper, we have presented a framework to build unified reusable configuration knowledge representation for IoT resources. The framework consists of (1) a unified configuration knowledge representation model for IoT resources; (2) a declarative and context-aware language to specify users’ requirements of IoT applications in terms of service category, data source and deployment node; (3) automatic recommendation of IoT resource configuration for a given context; (4) an incremental configuration knowledge acquisition mechanism based on a ripple down rules base.
To evaluate the feasibility and efficiency of the proposed framework, we implemented our system as a proof of concept prototype. As future work, we plan to (1) extend our recommender system with some recommendation algorithms; (2) extend automatic deployment features in our recommender system.

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