Inter-space Machine Learning in Smart Environments

Amin Anjomshoaa(✉) and Edward Curry

Lero – the Irish Software Research Centre, National University of Ireland, Galway, Ireland
{amin.anjomshoaa,edward.curry}@nuigalway.ie

Abstract. Today, our built environment is not only producing large amounts of data, but –driven by the Internet of Things (IoT) paradigm– it is also starting to talk back and communicate with its inhabitants and the surrounding systems and processes. In order to unleash the power of IoT enabled environments, they need to be trained and configured for space-specific properties and semantics. This paper investigates the potential of communication and transfer learning between smart environments for a seamless and automatic transfer of personalized services and machine learning models. To this end, we explore different knowledge types in context of smart built environments and propose a collaborative framework based on Knowledge Graph principles and IoT paradigm for supporting transfer learning between spaces.

Keywords: Smart environment · Knowledge graph · Transfer learning

1 Introduction

Humans spend a significant portion of their lifetime indoors and are actively pursuing the vision of an ideal built environment which encompass the emergence of utopian concepts such as smart city, smart building, and smart home. In order to maintain our comfort, we have equipped our buildings and spaces with diverse information systems and services powered by the Internet of Things (IoT), which are generating a huge amount of data. Recently, the front-runners of ICT industry are exploiting the power of artificial intelligence and machine learning techniques to advance virtual assistants that facilitate the interaction with IoT devices and space services such as thermal comfort and ambient assisted living [19] in private environments. Examples of such virtual assistants are Google Home, Amazon Alexa, Microsoft Cortana, and Apple Siri. In order to integrate any of these virtual assistants, the services of virtual assistants need to be calibrated and configured based on space-specific properties and semantics and are captured in various ways such as dedicated information resources, service compositions, sense-actuate cycles, and well-trained machine-learning models. This task usually involves intensive human interventions to understand the implicit

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semantics of space, devices, as well relevant information resources and services. For instance, an Amazon Echo user may use Amazon's voice service, Alexa, to control smart devices such as cameras, door locks, entertainment systems, lighting, and thermostats. Furthermore, end-users are able to compose new services and sense-actuate cycles based on one or more IoT devices to accomplish more complicated tasks.

IoT-based systems are typically built following a three-layer model (cf. 1) that consists of: (i) a sensing layer, which acquires the observation of interest from the environment; (ii) a context layer, which is concerned with context acquisition, modeling, and reasoning; and (iii) an actuate layer that triggers an action or invokes a service according to some predefined logic. The main effort required for automatic change management in a private IoT space is hidden in the context layer. Unlike the sense and actuate layers which typically undertake straightforward tasks, the creation and configuration of the context layer is a complicated task which is not necessarily based on a syntactic or deterministic model. Instead, it needs a deep understanding of incoming events as well as the context of those events. Currently, human cognition is necessary to interpret the incoming data from the sensor layer and add the missing semantics about the events and their context.

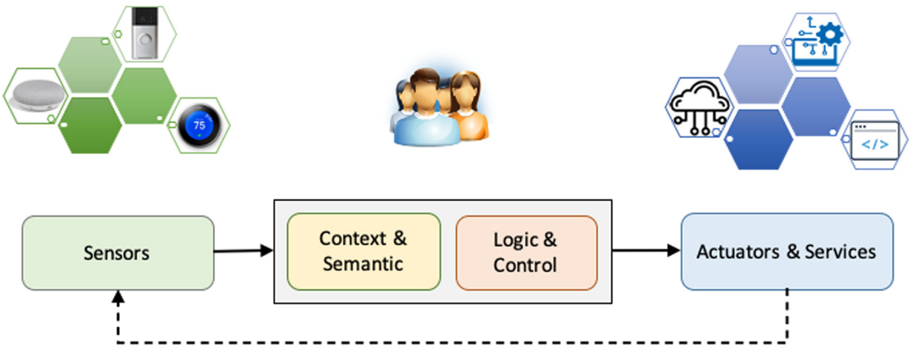

Fig. 1. Three-layer model of an IoT-based system including sensing, context, and actuation layers.

Additionally, in order to transfer the personalized services beyond the boundaries of private spaces, the technical details of sensing and actuation components needs to be adapted based on the smart nodes and IoT standards of the target space. For instance, in the thermal comfort scenario we might have different types of temperature sensors and control mechanisms to adjust the room temperature. While in one space we actuate the heater, in a second space the temperature might be controlled by opening and closing a vent. As such, we would need to adapt and customize the sensing and actuating layers in order to make personalized services transferable.

In summary, although human interventions for personalizing the smart environments work well, such methods may soon be infeasible due to the following challenges:

1. **Versatile IoT configurations:** Human contribution cannot cope with the ever-increasing number of IoT devices. By introducing new devices or applying changes to the smart environment, the configurations and rules needs to be revisited and checked. As such, we need a configuration management approach that supports flexibility, dynamicity, and incremental change in smart environments.
2. **IoT service transfer:** While users can manage, train, and configure the services in their private environment, it is not easy to transfer such configuration to semi-private spaces such as hotel rooms, cars, hospital rooms, open city spaces, and offices. For instance, suppose an individual has defined some rules to maintain his/her thermal comfort at home based on services such as motion detector, air conditioning system, and the body temperature from a wearable device. In order to achieve the same thermal comfort in a semi-private environment such as hotel room or office, the rules need to be adjusted based on the semantics and standards of the target spaces.
3. **Transfer learning:** The smart space services, embodied in machine learning models, are commonly associated with time-consuming and costly processes such as large-scale data collection, data labeling, network training, and fine-tuning models. Sharing and reuse of these elaborated models in a different space would facilitate the adoption of services for the inhabitants and accelerates the uptake of machine learning in smart building applications. The model adoption process, which is referred to as Transfer Learning, is commonly undertaken by a human who is able to understand the implicit semantics of spaces, devices, as well as the relevant information resources and services. Therefore, self-explaining and machine-understandable models are the key requirements to accelerate the transfer learning between smart spaces.

In this paper we introduce the concept of Inter-space learning which exploits efficient and economic realization of knowledge exchange and transfer learning between spaces. To this end, we will first introduce the different knowledge types in built environments and then explore the sharing and reuse of machine learning models within transfer learning scenarios.

2 Knowledge Types in Built Environment

Before discussing the Inter-space learning methods and concepts, we need to identify the different types of knowledge that are embodied in a physical space. Our built environment is made of various complex and interrelated systems and services that draws upon interdisciplinary areas such as economics, law, public policy, public health, management, geography, design, technology, and environmental sustainability. As such, the embodied knowledge in built environment comes in various types that cover different aspects of space information. The embodied knowledge ranges from simple facts and concepts such as basic space information to more complex knowledge types such as rules, procedures, and models. In order to use this knowledge effectively, part of this knowledge which is known as explicit knowledge is communicated through various mediums [10] and can be readily articulated, codified, stored, and accessed by human and machines [11].

Knowledge is a broad concept and has been extensively debated in philosophy for many centuries and still there is no universal agreement about its definition and different categories. However, due to the increasing interest in organizational knowledge and knowledge management systems, we need to take a pragmatic approach and define the knowledge types that are needed in the domains of interest to solve our day to day problems. Based on the existing works in knowledge management and knowledge management systems [1], we have identified five knowledge types, namely, Basic (Priori) knowledge, Inferred (Posteriori) knowledge, Procedural knowledge, Cognitive knowledge, and Descriptive Knowledge. These categories establish the basis of our inter-space learning framework and will be described in the following subsections.

As shown in Fig. 2, knowledge types are interrelated and may create new facts about the domain of interest. To this end, the inferred knowledge can be completed by applying rules to the basic knowledge, executing a procedure, or using cognitive models (e.g. machine learning models) to recognize new facts.

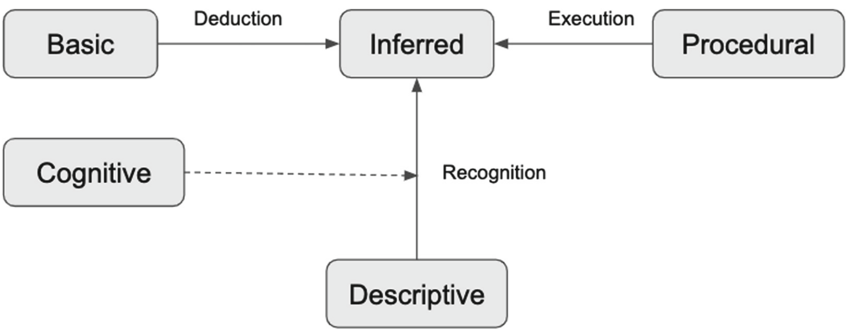

Fig. 2. Knowledge types and their inter-relations.

In the rest of this section we discuss these knowledge types and their corresponding learning objects in context of smart built environments.

2.1 Basic (Priori) Knowledge

In the context of the built environment, the basic knowledge is the explicit knowledge that covers various building artefacts and their relationships. Such knowledge can be readily assessed and acquired from the existing resources of a smart space and comprises various static space characteristics such as building elements, information models, and their physical and logical relationships. This information includes complex, multi-resolution, interrelated entities that are tightly connected to their surrounding environment. Identifying these components and their cross-links with surrounding entities such as people and devices will establish a preliminary base for enhancing various building processes.

Part of the basic knowledge of the built environment is currently captured via a wide array of Building Information Modeling (BIM) approaches of the Architecture, Engineering, and Construction (AEC) domain. Due to the complex nature of the built environment, there is no universal model that can capture all physical and functional requirements of buildings. As a result, there are several BIM standards and formats – each designed for specific building processes and use cases. Furthermore, the environments also include a growing number of IoT devices which form the virtual network of connected physical objects.

The basic knowledge of a smart built environment can be captured and documented in a number of ways. One such method is the use of ontologies and Linked Data where domain concepts and their relationships are represented by means of knowledge graphs. The knowledge graph provides a standardized descriptions of the physical (e.g. doors and windows, IoT devices), logical (e.g. neighbor-room and floor-room relationships), data streams, and virtual assets and their relationships. In order to establish these knowledge graphs, existing and well-known ontologies can be adopted and extended to fulfill the requirements of smart applications. For instance, in a smart building environment, we may reuse the Brick schema [5] that consists of an extensible dictionary of building terms and concepts, a set of relationships for linking and composing concepts together, and a flexible data model permitting seamless integration of Brick with other tools and databases.

2.2 Inferred (Posteriori) Knowledge

The basic knowledge can be extended by means of deductive reasoning, applying rules to existing facts, and use of cognitive models to process implicit knowledge. Furthermore, inference-based techniques can be used in discovering possible inconsistencies during the data integration processes. In semantic based and knowledge graph systems, the inference is commonly specified by means of semantic rules expressed by a description logic language. For instance, in a smart building environment semantic rules can be applied to real-time data streams of CO2 sensors to infer the space occupancy status.

2.3 Procedural Knowledge

This category of knowledge includes procedures or steps that are required to accomplish a task. For instance, the sense-actuate cycles in IoT-based solutions are simple procedures that connect sensors data to a specific task. Commonly, the creation and configuration of such procedures is a complicated task which is not necessarily based on a syntactic or deterministic model and is usually undertaken by human who has a profound understanding of incoming events as well as the context of those events.

Although the idea of connected things has opened up many possibilities for machine-to-machine communication, however these environments require an elaborated service layer around connected things in order to create smart environments. These services receive requests from hardware or software agents and process and analyze the input data according to their embedded logic to generate the appropriate output. In context of smart environments, the merge between data and services has led to the notion of data mashups. Using this analogy, the large amount of data produced by people, devices, buildings, and infrastructure streams between the processing nodes and services and the results are recycled back to the system. Efficient and intelligent programming of these data streams and services may turn spaces into even more productive entities.

2.4 Cognitive Knowledge

This type of knowledge includes information or sources of knowledge that cannot be explicitly defined and are acquired by observation and experimentation. An example of this type of knowledge is machine learning models that are taught to undertake complex tasks such as face recognition or energy optimizations using supervised, unsupervised, or reinforcement learning approaches. In context of smart built environments, these methods benefit from the huge amount of data in IoT-enabled spaces in their training processes which could yield significant profit over the lifetime of a building.

The cognitive models (machine learning models) can be refined and extended by technique such as transfer learning where a model trained on one task is re-purposed on a second related task. There are two main reasons why transfer learning is considered a key enabling technology in smart environments:

- In supervised machine learning approaches, we would need large training and test datasets in order to create reliable models. However, in many cases sufficient training and testing data does not exist.
- The real world is messy and contains various unpredicted scenarios that we have not encountered/considered during the training process. Including all exceptional cases and scenarios requires significant training which increases the model creation costs.

The high costs of creating machine learning models which also requires large amount of training and testing data sets, gives smart environments an incentive to reuse and re-purpose the existing models. For instance, in a smart environment the speech recognition model can be adopted and retrained in a new space to cope with the surrounding noise of the target space.

2.5 Descriptive Knowledge

This type of knowledge is declared in sentences, text documents, images and other formats that are not readily available to digital processes. Examples of this type of knowledge are safety guidelines of buildings, space history, images, and videos. In order to acquire explicit knowledge from such information, we would need advanced methods such as deep learning and machine learning to process and extract relevant information [24]. For instance, a video stream can be processed for inhabitant identification purposes or a text recognition system may be used to analyze the content of documents and semantically connect them to relevant resources.

3 Learning in Smart Spaces

This research aims to investigate the potential of communication and learning between smart environments for a seamless and automatic transfer of personalized services and applications. This process may range from simple sharing of data and information to more complex knowledge transfer method such as transfer learning where the knowledge gained in a specific space can be applied to a different space configuration. In this section, we will first explore the potential ways for communication between spaces for knowledge sharing and knowledge reuse purposes.

3.1 Space Knowledge Communication

Based on the introduced knowledge types in the previous section, we will now focus on the different methods for sharing and reuse of embodied knowledge in building spaces or zones. These communication methods are depicted in Fig. 3 and are classified as follows:

– The first and simplest method of communication between spaces is running queries on the explicit knowledge. Since the explicit knowledge can be articulated and codified, the spaces with a common understanding of domain concepts can formulate relevant queries based on common shared concepts (ontologies) and interpret the returning results in order to complete their inferred knowledge. For instance, two spaces that belong to the same thermal zone of a building can share the information about the corresponding Air Handling Unit (AHU) and its power meter.
– Procedures can be shared as a whole (black-box service on cloud) or get adopted and customized for use in context of the target space. As an example, consider a procedure that requires interaction with specific types of sensors/actuators or need to communicate with external services to accomplish a task. In order to adopt such procedures, we might need to replace the sensors and adjust its communications based on the resources available at the target space. For instance, in a temperature control scenario that includes a simple sense-actuate cycle, we need to adjust the procedure based on the available IoT services in the target space.
– Part of domain knowledge can be captured by elaborated models. These models are able to transform parts of the human's tacit knowledge into explicit

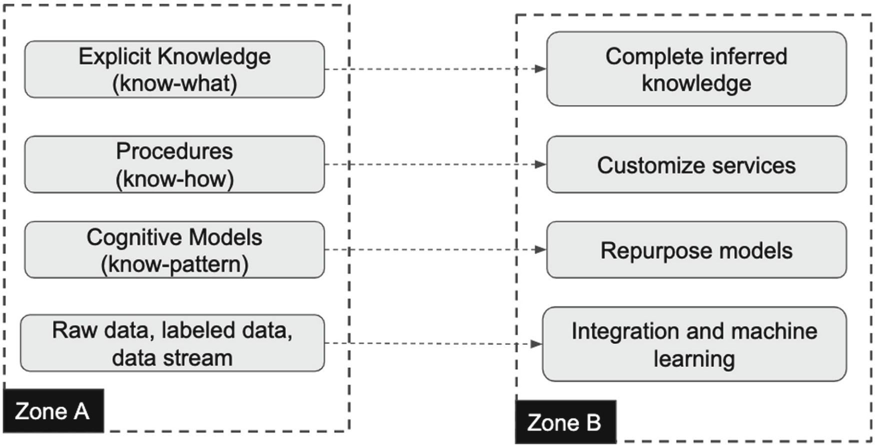

Fig. 3. Zone communication methods.

knowledge which can be used by machines. Machine learning models are examples of such knowledge acquisition method that facilitate sharing of cognitive-based approaches. Such models can be repurposed and retrained in the target zone in order to satisfy the contextual requirements. For instance, a speech recognition model can be adopted and repurposed to cope with the noise in the target space.

– A common type of communication between spaces is sharing data in different formats, frequencies, and structures. Such data could be in the form of raw data that is shared for data integration purposes or labeled data (e.g. images with labeled objects) for machine learning purposes.

There is already a handful of research work that exploits the power of semantic web, linked data, and knowledge graphs for capturing and conceptualization of information and procedures in smart environments. In the rest of this paper, we focus on the inter-space communication methods for cognitive knowledge and through a case study investigate the potential of transfer learning between spaces and zones.

4 Case-Study: Occupancy Prediction

In order to demonstrate the feasibility and effectiveness of transfer learning in smart built environments, we use an occupancy prediction use-case which plays an important role in energy efficiency applications of smart buildings. Counting space occupants can be implemented using various sensing technologies such as PIR sensors, visual cameras, Wi-Fi and Bluetooth enabled devices, and door sensors. Recently, there is an increasing interest to measure the occupant count based on environment sensors such as temperature, humidity, and CO2 level of target spaces. Due to the long response time and calibration errors, the environmental-based methods are not as accurate as other sensing methods such as visual cameras; however because of the privacy and cost concerns as well as the recent advances in machine learning approaches, these methods are gaining momentum. To this end, there are various research work for occupancy prediction based on environmental sensor data [4,17,21] that provide sophisticated methods based on a combination of sensor types to offer high accuracy prediction results. In our paper rather than creating high accuracy prediction results, we aim to demonstrate the sharing and reuse of knowledge between spaces. So, we use a simple occupancy prediction model based on the CO2 level of a source spaces and then will measure the efficiency of reusing these model reuse in a different space.

4.1 Dataset

We use an open dataset [18] that is collected via sensors on room-level occupant counts together with related data on indoor environmental indicators including airflow, CO2, relative humidity, illuminance, and temperature. The dataset comprises 44 full days, collated in the period of March 2018 to April 2019 for a lecture room and two study-zones in a public building in the University of Southern Denmark, Odense campus. Table 1 lists the spaces of this dataset and their attributes.

Table 1. Summary of target spaces.

Room ID	Room type	Size (m2)	Seating-capacity	Volume (m3)
Room-1	Lecture	139	84	461.48
Room-2	Study-zone	125	32	418.75
Room-3	Study-zone	125	32	418.75

Before using this data and in order to mitigate the long response time of CO2 sensor data, we have limited the study time to the building's peak hours (6:00 am to 14:00 pm) and aggregated the data to 30 min intervals. Then a collection of statistical metadata was calculated and added to the description of the dataset. We may use this metadata for finding top candidate models when a specific service such as occupancy prediction is offered by more than one space. For describing the statistical metadata, we use and extend the terms and relations defined by ML-Schema [16], an interchangeable format for description of machine learning experiments. ML-Schema will also provide us with a set of classes, properties, and restrictions for representing and interchanging information on machine learning algorithms, datasets, and experiments. Figure 4 depicts part of the knowledge graph that describes the dataset as well as statistical metadata.

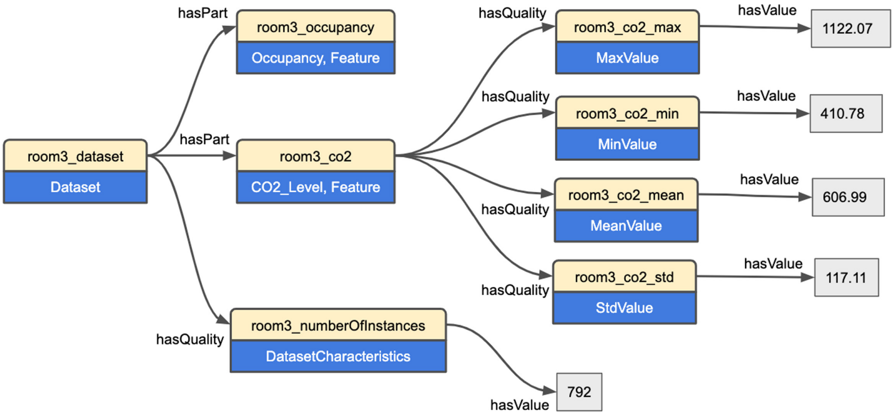

Fig. 4. Part of the knowledge graph describing dataset features such as occupancy, CO2, and their corresponding metadata.

4.2 Knowledge Graph

As described previously, the knowledge graph should include both the space information and the dataset description. So, in addition to the ML-Schema, we would also need a schema to describe metadata of smart spaces including sensors, subsystems and the relationships among them. To this end, we use the Brick schema [5] that is a uniform schema for representing metadata in IoT-enabled environments.

In the knowledge graph proposed in this research, we create a bridge between ML-Schema and Brick to describe dataset, building information, and machine learning processes. As depicted in Fig. 4, machine learning processes can be characterized based on their input data, output model, and model evaluation measures such as Mean Absolute Error (MAE) or Mean Squared Error (MSE) of learning processes. Furthermore, each model is dedicated to a specific task defined by ML-Schema which helps spaces to find the relevant models shared by other spaces. As such, the models are presented in a self-explainable and interpretable way to both human users as well as space agents (machines).

In the case of multiple competing models for transfer learning purposes, the system needs to assess the fitness of offered models based on the metadata of source and target spaces. This can be achieved by one or a combination of the following approaches:

– A number of spaces may have similar properties and use. As such, the models of a space that depend on those properties can be shared and reused by other similar spaces. The space similarity, depending on use case, can be characterized by features such as room's function, size, or capacity. In the case of our occupancy prediction model, rooms of the same size and capacity are expected to behave similarly.

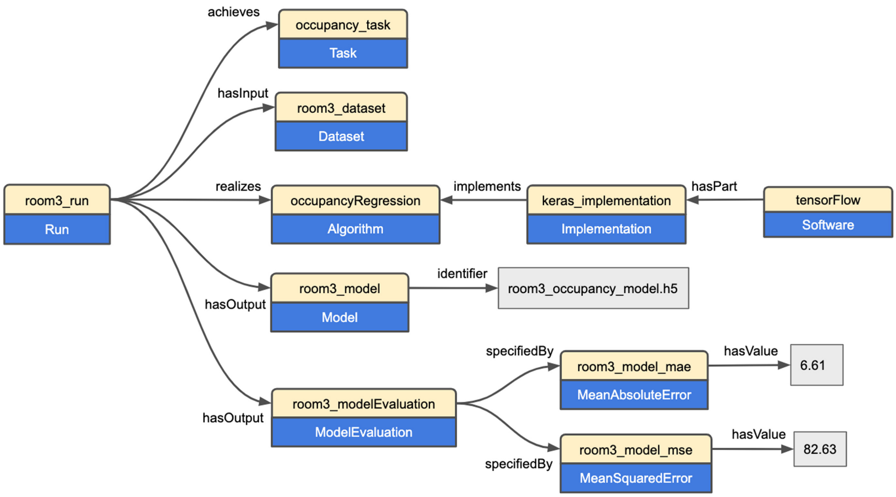

Fig. 5. Part of the Knowledge graph describing ML-Schema.

- Training dataset plays also an important role in the accuracy of model predictions. If the machine learning model is created based on a small or low variance feature, its behavior in a new space will be unpredictable. Since all such statistical metadata are included in the proposed knowledge graph, the space agent can compare the range of its input features to those of the training dataset of adopted model and make sure the model is adequately good for transfer learning purposes.
- The machine learning models are also characterized by their performance indicators. For instance, the loss indicator which is widely used in machine learning processes can be used for comparison and ranking of the available models for a specific task.

4.3 Transfer Learning

During the operation phase, buildings are now producing more data than ever before, such as energy usage statistics, utility information, occupancy patterns, scheduling information, and financial data. However, this information cannot be used directly for machine learning purposes and requires time-consuming processes for preparing and fine-tuning training datasets that are vital for creating high quality machine learning models. In the machine learning domain, transfer learning aims to eliminate the high cost of data preparation processes by sharing and reuse of pre-trained models.

In the proposed use case, we have used the CO2 time series of each room as input and created a simple logistic regression model [15] to predict the room occupancy count. Next, we use these models in other rooms and investigate their fitness and performance compared to the model trained by target room's data. Figure 6 depicts the performance matrix of these models on test dataset of each room. The rows in this matrix show the regression models and columns specify the applied test data.

As expected, the model performance should be best when it is applied to the test data of the room itself. Furthermore, the room with similar characteristics (e.g. size and volume) shows similar performances and as a result can adopt the models from each other. For instance, room-2 and room-3 in our use case have similar properties and also their training dataset is consistent (similar statistical indicators) and as shown in Fig. 6 the performances of transferred models are within an acceptable range. However, room-1 has different function and properties and as a result the performance of adopted models compared to its own model is not acceptable.

5 Related Work

Knowledge graph is a powerful tool for capturing digital representations of both physical and functional characteristics of buildings. They can play an important role in narrowing the physical-digital gap via applying a network of digital elements around our physical built environment for integration of brick-based (i.e. physical space and IoT devices) and bit-based (i.e. cyberspace and IT services) elements [14].

In order to build and populate the knowledge graph of smart environments, a number of methods and standards are introduced. For instance, the Industry Foundation Classes (IFC) developed by the BuildingSMART alliance [22] is one of the most mature Building Information Modeling (BIM) standards and defines an object-based hierarchy of building entities and concepts for data exchange and data sharing. In this context, several researches have proposed domain specific ontology schemas based on BIM and Linked Data principles for supporting the interoperability and data integration in smart built environments [3,8,20].

Although, the BIM standards provide a comprehensive description of buildings' physical elements and address a number of interoperability challenges between systems and services, but they fail to capture the relationship between static building information and real-time dynamic of IoT ecosystems in smart buildings [2]. To this end, the Brick schema [5] provides a broader coverage of concepts for smart buildings by standardizing semantic descriptions of the physical, logical and virtual assets in buildings and the relationships between them.

Recent advances in Knowledge graph [12] and machine learning domains has revealed their complementary nature and advantages of combining knowledge graphs and machine learning techniques [6]. More specifically, knowledge graphs and ontologies are introduced as key technologies for creating explainable and comprehensible machine learning models for both human and machines [13]. Furthermore, existing works [9,23] have shown the potential of transfer learning for IoT and edge devices but these approaches are not geared towards capturing the semantics of space, IoT devices, or the machine learning models.

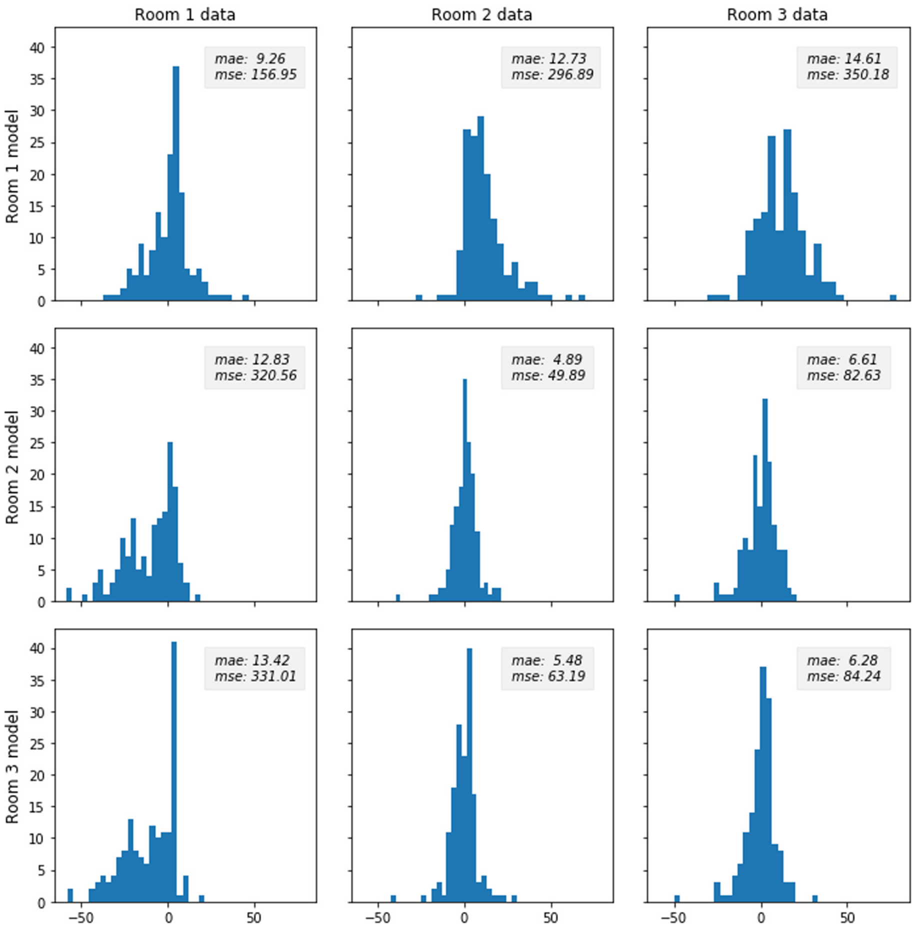

Fig. 6. Predicting space occupancy by self-trained model vs. transferred models. The histogram plot in each cell shows the distribution of errors for the occupancy counting task.

6 Conclusions and Future Work

Buildings as an integral part of urban settlements are being equipped with more IoT devices than even before. In this context, IoT industries and service providers strive to find more efficient ways to benefit from the growing IoT ecosystem and combine it with other available information resources in order to create smarter environments. In this research we discussed various knowledge types in built environments and described the relationship between them. Furthermore, we demonstrated that transfer learning based on building knowledge graphs can be effectively used in smart spaces. The presented showcase for occupancy prediction, shows the feasibility of this approach, however there are a number of challenges such as the fitness of adopted models and the efficacy of training datasets needs to be further investigated. As future work, we aim to explore the application of Real-time Linked Dataspaces [7] for enriching the context layer of IoT-enabled spaces and address the requirements of transfer learning use cases.

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