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ISEE: A Heterogeneous Information System for Event Explainability in Smart Connected Environments

Abstract

Smart connected environments as well as digital contents are more and more present in our daily life. The former monitors various data produced by sensors, while the latter contains valuable additional information (e.g., technical data sheets, maintenance reports, employee register). When an event occurs, users generally want to figure out why this event happened. Unfortunately, most information systems in connected environments do not combine sensor network data with document corpora. Consequently, users have to look for an event explanation by querying both complementary sources with different systems, which is indeed very tedious, time consuming and requires a huge compilation effort. In this article, we apply the 5W1H model ("What? Who? Where? When? Why? How?"), commonly used in question-answering, to bridge the gap between sensor networks and document corpora. Our framework entitled ISEE (Information System for Event Explainability) offers an original approach that (i) defines events along four dimensions, (ii) interconnects semantic information coming from sensor networks and documents with 5W1H connections, and (iii) provides to the user a set of preliminary event explanation according to 5W1H answers. A real motivating use-case based on a smart-building is presented and experimental results are discussed.

Keywords: Event explainability, Sensor, Document, Semantics, 5W1H, Heterogeneous Information System, Smart-building

1. Introduction

Due to their great potential in the improvement of safety, comfort, productivity and energy-saving, smart connected devices have become ubiquitous in our everyday lives, impacting different domains from hospitals, malls, farms and buildings to cities, vehicles and electrical grids.

5 Over the last decade, in order to boost even more life quality in smart connected environments, an untold number of research work has been conducted to propose additional services based on the exploitation of collected data [1]. Event detection is one of those services. Events can be defined

as "the real-world occurrences that unfold over space and time" [2]. In the literature, three main types of events are distinguished: (1) socio-cultural events that have an associated place, theme and audience (e.g., concerts, festivals, sports events); (2) news article events, which correspond to current information (e.g., Spain won the football world cup in 2010, several school closures caused by Covid-19); (3) events detected by devices such as sensors which monitor the physical world and indicate the triggering of a given phenomenon (e.g., fire detection, stroke detection for patients, air pollution detection). In this paper, we focus on the explainability of events detected by sensors (3), and more specifically those that occur in smart connected environments with heterogeneous information systems (IS) (i.e., document IS and sensor network IS). Let's take the example of a light wastage event in a smart building office (e.g., a light sensor detects luminosity level and triggers an alert if it's greater than 30 lux during night). The natural reaction of the smart building manager, when the alert occurs, is to try to figure out why it happened by querying various information sources (e.g., why was the event triggered? Was there anyone in the office when the event triggered? If not, who was the last person to enter the office?). However, to the best of our knowledge, there is no paper that aims to explain events that occur in smart connected environments, using both sensor network and document corpus data. To sum up, the limit of traditional approaches of event explainability in smart connected environments are as follows:

(i) **Data scope:** a wide spectrum of data dispersed across heterogeneous data sources with different structures, languages, semantics and versions (e.g., structured data tables in the sensor network IS and semi-structured or unstructured data sheets in document IS).

(ii) **Manual search:** existing sensor network information systems do not allow interconnecting sensor network and document corpus. It is up to the user to build these connections through multiple queries: first, the user has to query sensor network, then explore the interesting leads by querying many times the two data sources. The user could be overwhelmed by a huge amount of unnecessary data. Moreover, the user has also to reformulate his queries many times to refine the results until getting the correct event explanation, which is very tedious, time consuming and requires a huge compilation effort.

(iii) **Poorly structured results:** at the end of this process, the elements constituting the explanation are dispersed across various documents and sensor data (e.g., staff directory, records of employees assigned to the office, the office badge access report, a list of equipment that can produce light in the office). It is again up to the manager of the connected environment to sum up.

To overcome these limitations and build a well-structured event explanation, we found it very
40 interesting to apply the 5W1H technique in our context. The 5W1H [3] is an approach usually
used for the extraction of structured semantics from online news. In our context, 5W1H will allow
us to bring together heterogeneous data sources and select more efficiently relevant information by
driving the information retrieval process through the six questions (What? Who? Where? When?
Why? How?). Moreover, we assume that structuring the final explanation in the form of 5W1H
45 result will aim at insuring the simple, intuitive and user-friendly aspect of the event explanation.

In this paper, we propose ISEE (Information System for Event Explainability), an event ex-
plainability framework for smart connected environments with a heterogeneous information system
based on the 5W1H. Commonly, to build an event explanation, the framework has to: (a) express
one or multiple queries; (b) match sensor network and document collection data and select the
50 subset of relevant information; (c) construct and present results that can be easily understood by
the end user. In this paper, we focus exclusively on point (b). On one hand, we propose an ef-
ficient process for the interconnection of sensor networks and document collection data. And on
the other hand, we provide algorithms for retrieving and scoring relevant information in order to
explain the triggering of an event. The 5W1H will be the guiding principle of our proposal for
55 making semantic connections between sensor and document data, and computing explanation of an
event occurrence. Consequently, it leverages existing works such as event modelisation, information
retrieval (IR), semantic IR, and 5W1H question-answering. The originality of our proposal relies
on a context-aware (event-aware) semantic interconnection within an iterative filtering process for
sensor network and document corpus data. In what follows, we present a scenario that motivates
60 our proposal in Section 2. We describe the ISEE framework in Section 3. We present two experi-
ments in Section 4. Then, we present the state of the art in Section 5. Finally, Section 6 concludes
the paper and discusses the upcoming works.

2. MOTIVATING SCENARIO

We consider a real example of a four floors smart connected office building (Figure 1¹). Various
65 sensors (e.g., light, temperature, PIR motion sensors), mobile entities (e.g., people, laptops) and
static entities (e.g., air extraction system, doors, lamps) are deployed in the different rooms/floors.

¹Sample data available at: <https://citris-uc.org/about/sutardja-dai-hall/about-facilities/floorplans/>



Figure 1: The fourth floor of the SDH building sample

An associated information system also manages a large corpus of documents having different contents, structures and formats (e.g., company web site, employee data file, sensors and laptops technical sheets, maintenance reports). Let's now suppose that an abnormal energy consumption

70 has been detected in office 413 on the fourth floor last night. The building manager would like obviously to understand why it happened (e.g., why the event was triggered? Which employee is assigned to office no. 413? Who was the night watchman yesterday? Is there any other interesting data from other sensors? Have there been any recent reports of equipment malfunctions in the fourth floor?...). Using sensors IS, the manager is swamped with rooms raw data: CO2 concentration,

75 concentration, room air humidity, room temperature, luminosity, and PIR motion sensor data. Similarly, corresponding documentary resources are huge and numerous and an effective querying process difficult. Does the brightness detected by the luminosity sensor in office no. 413 at 8pm correspond to the visit of the night watchman Garret? Was Perrin the employee who forgot the light on when he left his office at 5pm? Is a lamp in office no. 413 defective? Considering all of the above, the

80 following challenges emerge: **(i)** How to fully exploit event data (sensor, time, location, etc.) in order to guide an information retrieval process? **(ii)** How to interconnect the two different data sources (sensor network and document corpus) in order to build event explanation? **(iii)** How to structure the final explanation in a simple, clear and user-friendly way? Furthermore, according to the context, the building manager may need an explanation within a more or less short period of

85 time. We will also consider this constraint by defining emergency levels. In the following section, we describe the ISEE proposal which addresses all the three above-mentioned issues.

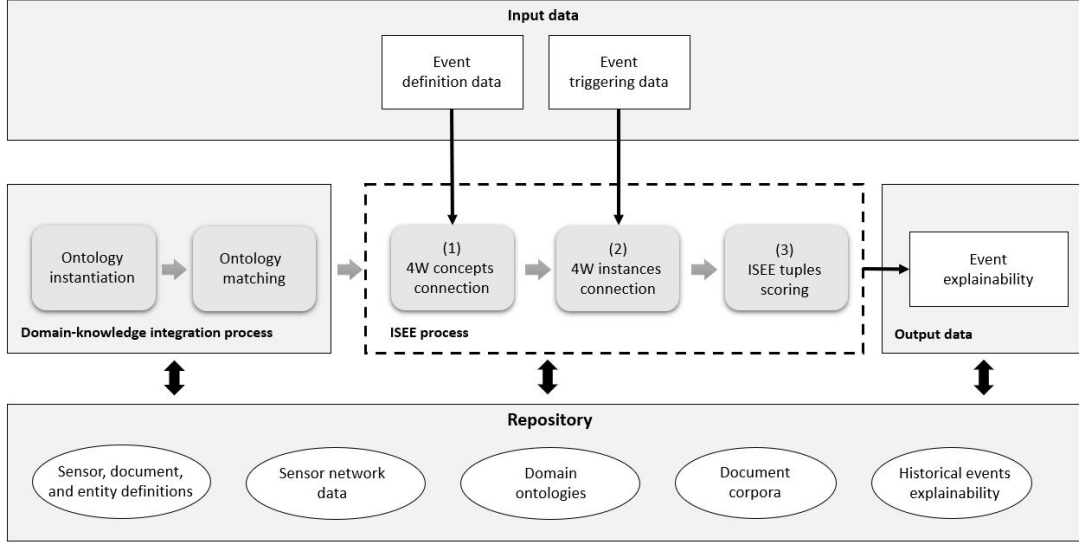


Figure 2: ISEE general overview

3. The ISEE Framework

As outlined previously, our environment consists of two information systems: a sensor network IS and a heterogeneous document corpus IS. We assume that we have several domain ontologies to model semantics of the sensor network [4] and document corpus data (e.g., human resources ontology and building domain ontology). Before the ISEE Framework (Figure 2) starts building explanation for events that trigger in the environment, a preliminary data integration step is necessary (*domain-knowledge integration process* in Figure 2). It consists of a two steps process:

- **Ontology instantiation:** this step aims to exploit the heterogeneous data sources (i.e., sensor network and document corpora data) in order to instantiate domain-ontologies (*Ontology instantiation* in Figure 2, Section 3.3.1).
- **Ontology matching:** ontology matching techniques [18] are used in order to build traditional alignments (e.g., equivalence, generalisation, and specialisation) between entities of domain ontologies (Ontology matching in Figure 2, Section 3.3.2).

Once the semantic model of the environment is built, the framework can start building explanations for events through the ISEE process (ISEE process, Figure 2). ISEE process is based on an iterative context-aware interconnection and filtering processes which are performed in three main steps:

1. **4W concepts connection:** a first network of a context-aware interconnections between concepts is built based on the event definition ((1) in Figure 2, Section 3.4.1) and the previously built traditional alignments.
2. **4W instances connection:** a second level of interconnections between instances is built based on the event triggering data ((2) in Figure 2, Section 3.4.2).
3. **ISEE tuples scoring:** the previously built graphs are parsed, ISEE explanation tuples are built and ranked according to a relevance score ((3) in Figure 2, Section 3.4.3).

In what follows, we formally define events and event characteristics in Section 3.1. Section 3.2 formally defines event explanation. We detail domain-knowledge integration process in Section 3.3. Finally, Section 3.4 presents the ISEE process.

3.1. Event definition

In this study, we define an event as a 4-dimensional space called *eSpace*. The event *eSpace* consists of *Features*, *Sources*, *Time*, and *Location* dimensions and an event data to represent sensor observations that help to detect the event. In what follows, we first define an event, then, we detail the definition of a dimension, finally, we define an event *eSpace*.

Definition 3.1. An **Event** e is defined as a 4-tuple $\langle id, l, eSpace, u \rangle$, where:

- id is the unique identifier of the event
- l is a label
- $eSpace$ is a 4-dimensional space that defines the event components as a set of dimensions (cf. Definition 3.3) and event-related data
- u is a level of urgency assigned to e where $u \in \{low, moderate, high\}$ ■

For example, a light wastage event can be defined as follows:

$LightWastageEvent : \langle 1, 'LightWastage', eSpace, 'low' \rangle$

The level of urgency here dictates the required level of event explanation based on the user preference. For instance, if $u = low$ (i.e., the user can wait a certain period of time before receiving the explanation) then one could fully explain the event although the processing time is significant.

However, if $u = high$ (i.e., there is an urgent need for the explanation) the explanation should be
130 light in order to return quick results to the user.

Definition 3.2. An **Event Dimension** d is defined as a 5-tuple $\langle id, o, C, R, C_d \rangle$, where:

- id is the unique identifier of the dimension
- o is the origin concept which best reflects d
- C is the set of concepts related to d
- 135 – R is the set of relations related to d
- C_d is the set of constraints associated with d ■

For example, *Features* and *Time* dimensions of the light wastage event can be defined as follows:

Features: $\langle 3, \text{Luminosity}, \{\text{Cost}, \text{Energy}\}, \{\text{hasFeature}\}, \{\text{Lumens} > 30\} \rangle$

Time: $\langle 5, \text{TimeInterval}, \{\text{TemporalEntity}, \text{TimeInstant}\}, \{\text{inDateTime}, \text{inTemporalPosition}\},$
140 $\{\text{timestamp } duration \text{ 1hour}, \text{timestamp } includedIn [07:00:00pm, 07:00:00am]\} \rangle$

Note that qualitative and quantitative operators are used to define constraints on such dimensions [4]. For example, *includedIn* and *duration* are operators dedicated to temporal data (i.e., qualitative operators) whereas $>$ is an operator for numeric data (i.e., quantitative operators).

Definition 3.3. An **Event Space** $eSpace$ is defined as a 6-tuple $\langle id, \text{Features}, \text{Sources}, \text{Time},$
145 $\text{Location}, I \rangle$, where:

- id is the unique identifier of the event space
- *Features* is the dimension describing the event features
- *Sources* is the dimension describing the event sensor
- *Time* is the dimension describing the event temporal data
- 150 – *Location* is the dimension describing the event spatial data
- I is the set of event instance data.

I is empty when the event is defined, then data tuples are inserted every time the event is triggered. $I = \{ \langle id_1, Data_1 \rangle, \dots, \langle id_p, Data_p \rangle \}$, $id_{i \in \{1, p\}}$ is the event instance id and $Data_{i \in \{1, p\}}$

is the set of sensor observations that triggered the event. $Data_{i \in 1, p} = \{obs_1, \dots, obs_q\}$, $obs_{i \in 1, q} = \langle id_{obs}, sensor, time, location, value \rangle$. id_{obs} , $time$, $location$ and $value$ are the observation id, time, location and value respectively. $Sensor$ is the sensor which made the observation. ■

For example, the light wastage event space could be defined as follows:

$eSpace_{LightWastage} : \langle 2, \text{Features}, \text{Sources}, \text{Time}, \text{Location}, I \rangle$

- Features: $\langle 3, \text{Luminosity}, \{\text{Cost}, \text{Energy}\}, \{\text{hasFeature}\}, \{\text{Lumens} > 30\} \rangle$
- Sources: $\langle 4, \text{LightSensor}, \{\text{LightingSystem}, \text{Lamp}\}, \{\text{senses}, \text{makesObservation}\}, \{\} \rangle$
- Time: $\langle 5, \text{TimeInterval}, \{\text{TemporalEntity}, \text{TimeInstant}\}, \{\text{inDateTime}, \text{inTemporalPosition}\}, \{\text{timestamp } duration \text{ 1hour}, \text{timestamp } includedIn [07:00:00pm, 07:00:00am]\} \rangle$
- Location: $\langle 6, \text{Location}, \{\text{Coordinate}, \text{Position}, \text{Floor}, \text{Room}, \text{SpacialArea}\}, \{\text{hasLocation}, \text{hasAssignedOffice}\}, \{\} \rangle$
- $I : \langle \langle 7, \{\langle 36145, \text{lightSensor826}, 28/08/13 19:00:00, \text{Office_413}, 62 \rangle, \dots, \langle 36191, \text{lightSensor826}, 28/08/13 20:00:00, \text{Office_413}, 68 \rangle \} \rangle \rangle$

Note that, before defining events, all components of the environment are defined and integrated into the information system. In our context, the main components of the environment are sensors, entities (e.g., people, laptop) and documents (e.g., equipment technical data sheets, employee records). For those who are interested, the definitions are described in our previous paper [5].

3.2. Event explainability

In this section, we define event explanation in our context and give some examples. As already explained in Section 3.1, the user can assign three different levels of urgency to the event (i.e., low, medium and high). According to one level of urgency, the framework must return an explanation that corresponds to the user need in terms of content and waiting time. Hence, we propose three different levels of explanation, namely *raw event explanation* e_r , *medium event explanation* e_m , and *full event explanation* e_f which correspond respectively to high, medium and low event urgency.

- (i) **Raw event explanation:** this first level of explanation contains the event triggering data. It aims to provide the user with necessary data for rapid decision-making when the event explanation urgency is high (e.g., fire event). Raw event explanation is built based on

the processing of the corresponding event instance (i.e., a tuple $\langle id_i, Data_i \rangle$ of the set of event instance data I , Definition 3.3).

Definition 3.4. A raw event explanation e_r is defined as a 4W1H tuple. It is formalized as follows e_r : $\langle What, Who, When, Where, How \rangle$, where:

- 185 – *What* is the event feature
- *Who* is the sensor which triggered the event
- *When* is the event triggering time
- *Where* is the event triggering location
- *How* is the set of observations from $Data_i$ that triggers the event ■

190 The following describes an example of a raw explanation of the light wastage event:

e_r : **What:** Luminosity,
Who: LightSensor826,
When: 28/08/13 20:00:00,
Where: Office_413,
195 **How:** $\{ \langle 36145, \text{lightSensor826}, 28/08/13 19:00:00, \text{Office_413}, 62 \rangle, \dots,$
 $\langle 36191, \text{lightSensor826}, 28/08/13 20:00:00, \text{Office_413}, 68 \rangle \}$

As you can see in this example, the *How* field contains all the observations that triggered the event. These observations comply with the constraints specified in the light wastage event definition (Section 3.1): light levels are above 30 lux which corresponds to the constraint on the *Feature* dimension ($Lumens > 30$) and observation times are on a one-hour time slot after the working hours which corresponds to the constraints on the *Time* dimension (timestamp *duration* 1hour, timestamp *includedIn* [07:00:00pm, 07:00:00am]).

(ii) **Medium event explanation:** this level of explanation incorporates the raw explanation and adds a *Why* field. When an event occurs, there are one or many entities in the environment that contributed to its triggering. The *Why* field is constituted of 4W1H tuples, each detailing information about one of these entities. The 4W1H tuples are expressed in the form of concepts (e.g., Employee, Office, LightingSystem) without specifying exactly which instances (e.g., Roland.Perrin, Office413, Lamp45) are actually related to the event that was triggered.

Definition 3.5. A medium event explanation e_m is composed of the raw event explanation e_r and a *Why* field. It is formalized as follows $e_m: \langle e_r, Why \rangle$. Thus, e_m constitutes a 5W1H tuple $e_m: \langle What, Who, When, Where, How, Why \rangle$, where:

- *What, Who, When, Where* and *How* are the five fields that constitute the *raw event explanation* e_r (Definition 3.4)
- The *Why* field is defined as a set of 4W1H tuples, $Why: \{t_1, t_2, \dots, t_n\}, t_{i \in 1, n}: \langle m_{what}, m_{who}, m_{when}, m_{where}, m_{how} \rangle$, where:
 - * m_{what} denotes the set of concepts describing entities that may trigger the event
 - * m_{who} is a concept identified as responsible for the event triggering
 - * m_{when} is the set of temporal concepts that links m_{who} to the event
 - * m_{where} is the set of spatial concepts that links m_{who} to the event
 - * m_{how} is one or several triples: $\langle m_{who}, predicate, object \rangle$ which determine the way m_{who} has contributed to the event triggering. Here, the *predicate* is the property connecting m_{who} to an *object* and $object \in m_{what}$. ■

For example, the medium explanation of the light wastage event could be represented as follows (the concepts are shown in blue):

$e_m: \langle e_r, \{ \langle m_{what}: \{\text{Lamp}\},$
 $m_{who}: \text{Employee},$
 $m_{when}: \{\text{TemporalEntity}\},$
 $m_{where}: \{\text{Office}, \text{MeetingRoom}, \text{BreakRoom}\},$
 $m_{how}: \{ \langle \text{Employee}, \text{turnsOn}, \text{Lamp} \rangle, \langle \text{Employee}, \text{turnsOff}, \text{Lamp} \rangle \}, \dots \rangle$

e_r is the raw event explanation that has been illustrated previously. The following tuple, within the *Why* field, represents a potential explanation of the light wastage event. The construction of such tuples will be detailed in Section 3.4.1.

(iii) **Full event explanation:** Similarly, the full event explanation e_f incorporates the medium event explanation e_m enriched by a new *Why* field (i.e., Why') containing additional details. This Why' field is mainly based on event triggering data (Section 3.4.2). More

precisely, it consists of a set of candidate instances corresponding to concepts previously mentioned in e_m associated with a score.

Definition 3.6. A full event explanation e_f is represented as follows: $e_f: \langle e_m, Why' \rangle$. The Why' field is defined as a set of 4W1H tuples with scores, $Why' : \{t'_1, t'_2, \dots, t'_m\}, t'_{i \in 1, m}: \langle f_{what}, f_{who}, f_{when}, f_{where}, f_{how}, f_{score} \rangle$ where the five first elements are instances which correspond to e_m concepts and f_{score} is a value between 0 and 1. ■

For example, the full explanation of the light wastage event could be represented as follows (concepts and instances are shown in blue and purple respectively):

$e_f: \langle e_m,$
 $\langle f_{what}: \{\text{Lamp:L014, Lamp:L015}\},$
 $f_{who}: \text{Employee:Roland.Perrin},$
 $f_{when}: \text{TemporalEntity:28/08/13 18:32:50},$
 $f_{where}: \text{Office:Office413},$
 $f_{how}: \{\langle \text{Employee:Roland.Perrin, turnsOn, Lamp:L014} \rangle, \langle \text{Employee:Roland.Perrin, turnsOn, Lamp:L015} \rangle\},$
 $f_{score}: 0.83 \rangle, \dots \rangle$

The *When* and *Where* instances correspond to the office assigned to the employee Roland Perrin and the time at which he left this office. The score calculation metric will be detailed later in Section 3.4.3.

To summarize, our ISEE framework aims at building event explanation in smart connected environments based on event definition and triggering data. To structure the event explanations, the ISEE framework offers three different levels of explanation (i.e., raw, medium and full event explanation) that take their inspiration from the 5W1H model [6]. We synthesize all these elements in our event explainability model called ISEE model (Figure 3). It illustrates the life cycle of an event (i.e., event definition, event triggering and event explanation) and details the connections between the different classes. The ISEE process detailed in Section 3.4 aim at instantiating the classes of the third layer of this model (i.e., event explanation layer).

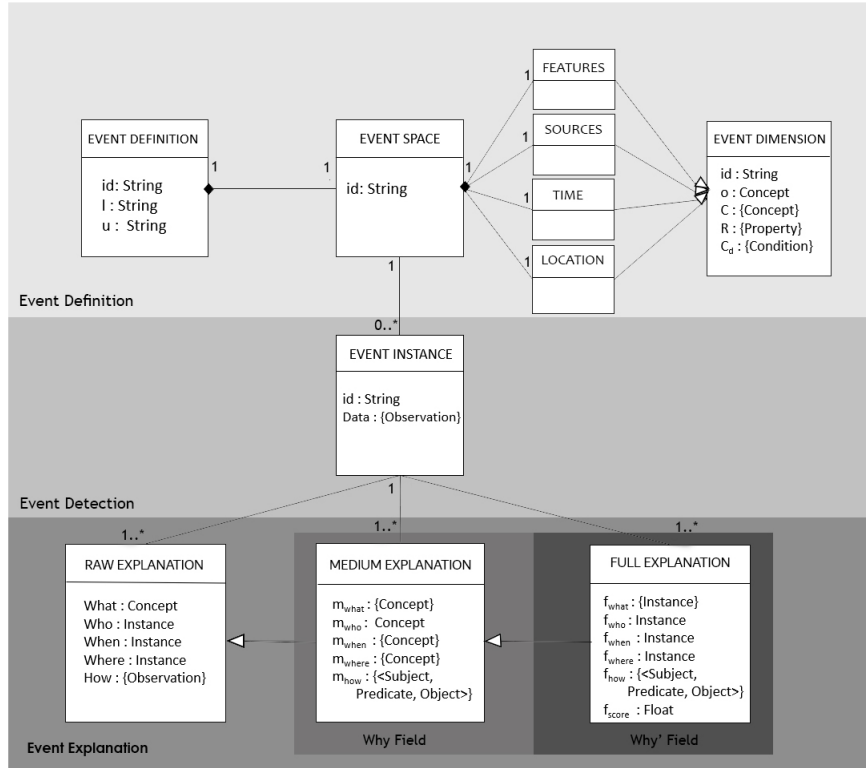


Figure 3: The ISEE model

3.3. Domain knowledge integration process

265 Our ISEE framework (Figure 2) is based on the assumption that parsing semantic interconnec-
 tions between domain ontologies using event definition and triggering data, will enable building a
 novel and detailed event explanation. In our context, ontologies are domain ontologies that cover
 heterogeneous knowledge (i.e., those related to the environment, the sensor network and the docu-
 ment corpus). The first step of domain-knowledge integration process (Section 3.3.1) aims at
 270 instantiating these ontologies using sensor network and document corpus data. Then, the ontology
 matching process (Section 3.3.2) performs a back-office ontology matching process between domain
 ontologies to build traditional alignment relations (i.e., equivalence, generalization and specifica-
 tion). In this section, we present and detail the two steps of domain knowledge integration process.

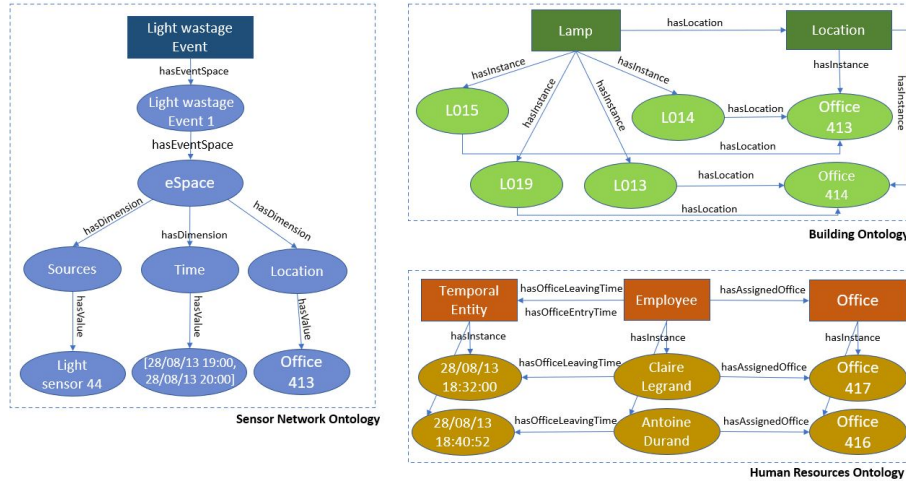


Figure 4: An example of ontology instantiation

3.3.1. *Ontology instantiation*

275 The main obstacle that has to be faced when trying to find an event explanation is the barrier that separates information systems dealing with sensor network data and those dealing with document corpus data. To address this problem, we rely on ontologies to build a semantic model of the environment, then, ontology alignment techniques to connect them. The ontologies will allow us to describe the semantics of the domain as a graph of concepts and relations. To populate

280 these ontologies with the raw data produced by sensors or extracted from text files, instantiation (or population) techniques [7, 8] are used. Ontology instantiation process consist in adding new instances of concepts and relations into an existing ontology. For example in Figure 4, we can see that the concept *Employee* has two instances *Claire Legrand* and *Antoine Durand*. These two instances could be extracted, for example, from the employee record of the building office.

285 Two main approaches are used in the literature for ontology instantiation: (1) algorithmic/heuristic based approaches [9, 10, 11] which usually involve NLP techniques, predefined mapping rules and human intervention for control and validation; (2) machine learning-based approaches [12, 13, 14] which also use NLP techniques associated with annotation methods from the semantic web. In our context, we used an algorithm-based approach, further details are presented in Section 4.

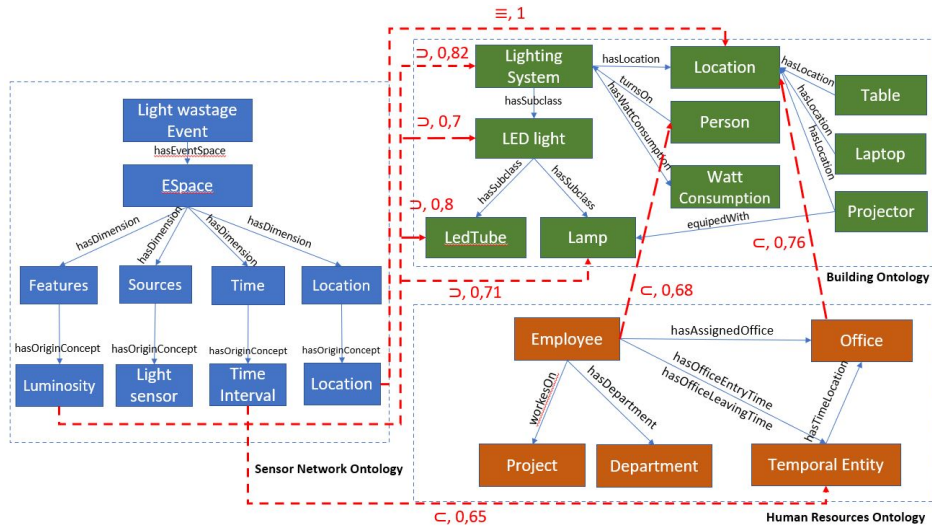


Figure 5: An example of ontology alignments

290 3.3.2. *Ontology matching*

As stated earlier, the second step of domain-knowledge integration process (Figure 2) aims at aligning the concepts of domain ontologies and the sensor network ontology. These connections are built in back-office independently of the event triggering data. They constitute the backbone of our ISEE framework and allow navigating from the event into the concepts of domain ontologies. We
 295 detail this process in Algorithm 1.

Several alignment techniques can be used [15, 16]. The system gives the user the flexibility in choosing the alignment method. This is represented in the algorithm as a function f . Algorithm 1 runs through all ontologies and computes the semantic similarity between each couple of concepts using the function f (Algorithm 1, line 6). If the confidence score of the correspondence is higher
 300 than a threshold, then the correspondence is added to the final set of results (Algorithm 1, lines 7-9). For example, in Figure 5, we can see that the pair of concepts *Luminosity* and *LightingSystem* are aligned with a specialisation relation (\supset) that has a high confidence score (i.e., 0.82). The correspondence $\langle Luminosity, \supset, LightingSystem, 0.82 \rangle$ is returned within the results. Note that, not all correspondences are shown in Figure 5, some were omitted for the sake of clarity.

Algorithm 1 Domain-ontologies matching

input : $O \leftarrow$ Sensor network and document corpora ontologies

$f \leftarrow$ An alignment function

output: A set of correspondences

```
1 Result  $\leftarrow$  {}
2 for each  $o_i$  in  $O$  do
3   for each  $concept_p$  in  $o_i$  do
4     for each  $o_j$  in  $O$ , with  $j > i$  do
5       for each  $concept_q$  in  $o_j$  do
6          $\langle$ correspondanceType, score $\rangle \leftarrow f(\text{concept}_p, \text{concept}_q)$ 
7         if score  $\geq$  Threshold then
8           Result  $\leftarrow$  Result  $\cup$   $\langle$ concept $_p$ , correspondanceType, concept $_q$ , score $\rangle$ 
9         end
10      end
11    end
12  end
13 end
14 return Result
```

305 3.4. ISEE process

In this section, we present and detail the implementation of the ISEE process (Figure 2). The first step of ISEE process (Section 3.4.1) aims to build a network of *What, Who, When and Where labeled semantic interconnections* between the event and relevant concepts of the different ontologies. The second step (Section 3.4.2) performs a second filtering process at the instance level, to keep
310 only those related to the triggered event. Based on this set of instances, a second network of What, Who, When and Where semantic interconnections is built. Finally, the last step (Section 3.4.3) parses the previous semantic networks, in order to score all the corresponding *ISEE* tuple candidates which will be returned within the triggered event explanation.

3.4.1. Concept level semantic interconnections

315 Based on the previously built ontology alignments, Step 1 of the ISEE process (Figure 2) aims at linking an event definition with concepts of the knowledge repository. These semantic interconnections are used to build the medium event explanation (Definition 3.5). We detail this step in Algorithm 2.

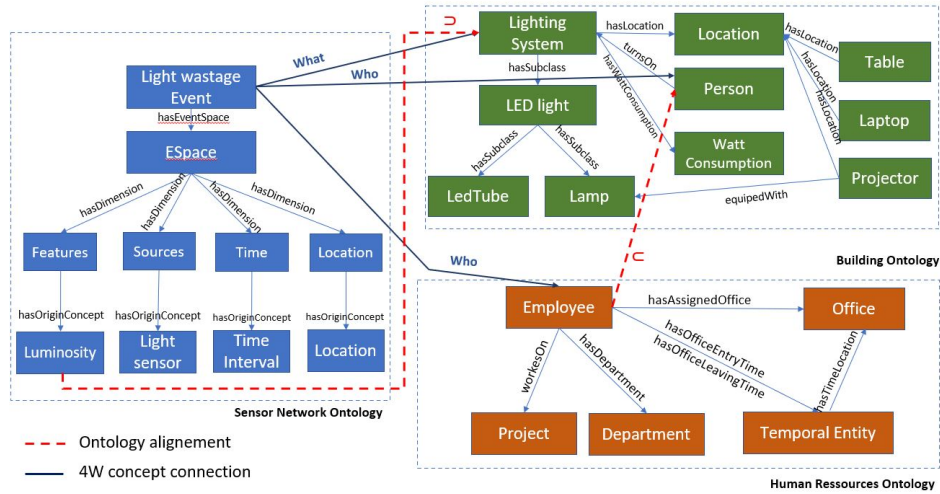


Figure 6: An example of What and Who concept connections

In order to build the *What*, *Who*, *When* and *Where* labeled interconnections, we use the align-
 320 ments produced by domain-knowledge integration process (Section 3.3.2) and the concepts repre-
 senting each of these 4 dimensions in the sensor network ontology (Algorithm 2, lines 1-8). For
 example in Figure 6, the *Feature* dimension of the *Light wastage* event is represented by the concept
Luminosity. Besides, the concepts *Luminosity* and *Lighting System* are aligned via a specialisation
 relation (represented in red). Thus, a *What* labeled semantic connection is built between the *Light*
 325 *wastage* event and the concept *Lighting System*. The same process is computed for the *Time* and
Location dimensions. To build the *Who* labeled semantic connections, which link the event to
 the concepts responsible of its triggering, we use the concepts previously connected to the event
 through the *What* labeled semantic connections (e.g., *Lighting System* concept) and we parse their
 direct neighbours (Algorithm 2, lines 9-17). For example, the *Lighting System* concept has three
 330 neighbours: *Location*, *Person* and *WattConsumption* concepts. Thus, a *Who* labeled semantic con-
 nection is then built between *Light wastage* event and the *Person* concept. Moreover, as concepts
Person and *Employee* were previously linked via a specialisation relation, a *Who* labeled semantic
 connection is also built between the *Light wastage* event and the *Employee* concept. For the sake
 of simplicity, we do not detail here all the *What* and *Who* labeled semantic interconnections.

Algorithm 2 4W concept matching

```
input :  $O \leftarrow$  sensor network and document corpora ontologies
         $ResultStep1 \leftarrow$  sensor network and document corpora ontology alignments from Algorithm 1
         $event \leftarrow$  event definition
         $Entities \leftarrow$  the set of concepts that represent environment entities

output: A set of triples with What, Who, When, and Where as predicates
1  $Result \leftarrow \{\}$ ,  $o_{what} \leftarrow event.eSpace.Features.o$ ,  $o_{who} \leftarrow event.eSpace.Sources.o$ 
2  $WhatConcepts \leftarrow GetAlignedConcepts(o_{what}, ResultStep1) \cup GetAlignedConcepts(o_{who}, ResultStep1)$ 
3 for each  $c_{what}$  in  $WhatConcepts$  do
4   |  $Result \leftarrow Result \cup \langle event.id, What, c_{what} \rangle$ 
5 end
   /* do the same for the Time and Location dimensions */
6  $WhoConcepts \leftarrow \{\}$ 
7 for each  $c_{what}$  in  $WhatConcepts$  do
8   |  $WhoConcepts \leftarrow GetNeighbourConcepts(c_{what})$ 
9   | for each  $c_{who}$  in  $WhoConcepts$  do
10  |   | if  $c_{who}$  in  $Entities$  then
11  |   |   |  $Result \leftarrow Result \cup \langle event.id, Who, c_{who} \rangle$ 
12  |   |   |  $AlignedWhoConcepts \leftarrow GetAlignedConcepts(c_{who}, ResultStep1)$ 
13  |   |   | for each  $c$  in  $AlignedWhoConcepts$  do
14  |   |   |   |  $Result \leftarrow Result \cup \langle event.id, Who, c \rangle$ 
15  |   |   |   end
16  |   |   end
17  |   end
18  end
19 end
20 return  $Result$ 
```

335 **3.4.2. Instances level semantic interconnections**

Event triggering provides a lot of interesting information, notably the spatio-temporal context (e.g., the time and the location of the light wastage event, the list of equipment that can produce light in Office 413, the office badge access report, etc.). Based on this information and on the output of Algorithm 2 (4W concept connections), Step 2 of ISEE process aims at linking a triggered event with instances related to the previously filtered concepts. These semantic connections are then used to build the full event explanation (Definition 3.6). We detail this process in Algorithm 3.

To build the *Who*, *When* and *Where* connections at the instance level, the instances of the concepts previously interconnected to the event, through the *Who* semantic connections, are parsed to select those having a location and a time that is closed to the event triggering (Algorithm 3, lines 2-14). For example, in Figure 7, the concept *Employee* is considered because it has a *Who* semantic

345

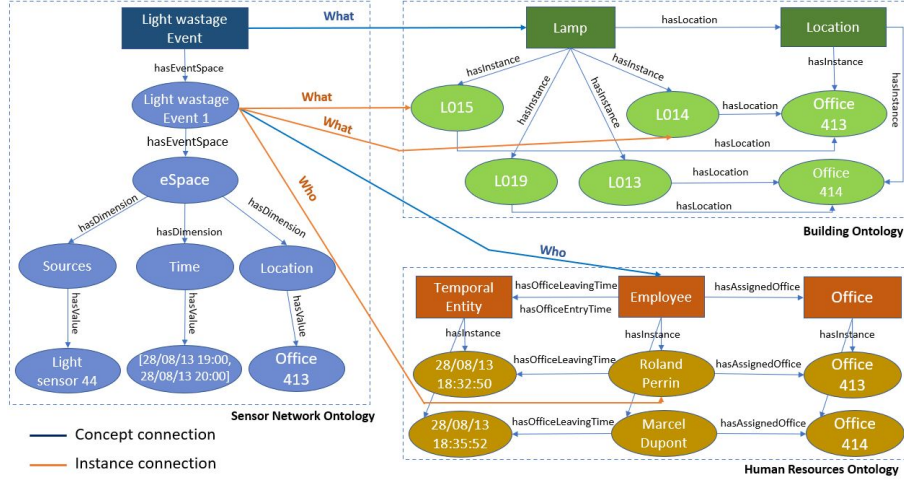


Figure 7: An example of a 4W instance connection

connection (blue arrow) with the event. The instance *Roland_Perrin* of the *Employee* concept is selected because this employee left Office 413 one hour before the event was triggered (using the two triples $\langle \text{Roland_Perrin}, \text{hasOfficeLeavingTime}, 28/08/13\ 18:32:50 \rangle$ and $\langle \text{Roland_Perrin}, \text{hasAssignedOffice}, \text{Office413} \rangle$). Consequently, a new *Who* labeled connection at the instance level (pink arrow) is built between the *Light wastage* event and the filtered instance *Roland_Perrin*. Of course, the *When* and *Where* connections are also built between the *Light wastage* event, *Office 413* and the time instance *28/08/13 18:32:50* respectively. In Figure 7, we do not show the *When* and *Where* connections for visibility reasons. Obviously, in Figure 7, we do not create other *Who* labeled connection at the instance level as the other employees were not in the proper office at the right time. To build *What* semantic connections at the instance level, the approach is similar to the *Who* semantic connections presented previously. Actually, the instances of the concepts previously interconnected to the event, through the *What* semantic connections, are parsed to select those having a location and a time that is closed to the event triggering (Algorithm 3, lines 15-25). For example in Figure 7, the concept *Lamp* is considered because it has a *What* semantic connection (blue arrow) with the event. The two instances *L014* and *L015* of the *Lamp* concept are selected because they are located in the same place as the event (i.e., *Office413*). Consequently, a new *What* labeled connection at the instance level (pink arrow) is built between the *Light wastage* event and the filtered instances *L014* and *L015*. Of course, the instances *L013* and *L019* of the *Lamp* concept

are not considered because they are not located in the same place as the event.

365 Note that for both *Who* and *What* semantic connections, we selected instances that are closed to the spatio-temporal information related to the triggered event thanks to its *Time* and *Location* dimensions. We select such instances even if only one of the two dimensions matches (i.e., if it satisfies only the temporal dimension or only the spatial one).

Algorithm 3 4W instance matching

```

input :  $O \leftarrow$  sensor network and document corpora ontologies
         eventTime, eventLocation  $\leftarrow$  event triggering time and location
         Result_step2  $\leftarrow$  What, Who, Where and When labeled triples from Algorithm 2
output: A set of triples with What, Who, When, and Where as predicates
1 Result  $\leftarrow$  {}
2 WhoConcepts  $\leftarrow$  GetWhoConcepts(Result_step1)
3 for each  $c_{who}$  in WhoConcepts do
4   WhoInstances  $\leftarrow$  GetInstances( $c_{who}, O$ )
5   for each  $i_{who}$  in WhoInstances do
6     Track  $\leftarrow$  GetTracks( $i_{who}$ )
7     selectedTrack  $\leftarrow$  SelectTrack(Tracks, eventTime, eventLocation, Threshold)
8     if selectedTrack NOT Null then
9       Result  $\leftarrow$  Result  $\cup$   $\langle$  event.id, Who,  $i_{who}$   $\rangle$ 
10      Result  $\leftarrow$  Result  $\cup$   $\langle$  event.id, When, selectedTrack.time  $\rangle$ 
11      Result  $\leftarrow$  Result  $\cup$   $\langle$  event.id, Where, selectedTrack.location  $\rangle$ 
12    end
13  end
14 end
15 WhatConcepts  $\leftarrow$  GetWhatConcepts(Result_step2)
16 for each  $c_{what}$  in WhatConcepts do
17   WhatInstances  $\leftarrow$  GetInstances( $c_{what}, O$ )
18   for each  $i_{what}$  in WhatInstances do
19     Track_what  $\leftarrow$  GetTracks( $i_{what}$ )
20     selectedTrack_what  $\leftarrow$  SelectTrack(Tracks, eventTime, eventLocation, Threshold)
21     if selectedTrack_what NOT Null then
22       Result  $\leftarrow$  Result  $\cup$   $\langle$  event.id, What,  $i_{what}$   $\rangle$ 
23     end
24   end
25 end
/* The instances connected to the event through 4W connections are used to instantiate the Why class */
26 return Result

```

3.4.3. Score based ISEE tuples identification

Step 3 of the ISEE process (Figure 2) aims at scoring each event explanation (i.e., ISEE tuples). ISEE tuple contains *What, Who, When, Where, How and Why*’ fields (Definition 3.6).

The *Why*' field is the one that explains the event and details the information about the candidates of the explanation. Therefore, the ISEE tuples score calculation will focus on this field. Algorithm 4 computes iteratively each *Why*' field and score it (line 3). The score calculation is based on four evaluation criteria, namely, the completeness (*comp*) which denotes the number of 4W1H questions answered by the *Why*' field, the diversity (*diver*) that counts the number of what instances connected to the event explanation, the confidence score (*conf*) summarizing the original alignment scores and the spatio-temporal proximity (*prox*) of the explanation. Hence, we propose the following scoring formula:

$$\text{Score}_{\text{tuple}} = \frac{1}{\alpha + \beta + \gamma + \delta} * (\alpha.\text{comp} + \beta.\text{diver} + \gamma.\text{conf} + \delta.\text{prox})$$

370 – $\alpha, \beta, \gamma, \delta$ are weighting coefficients, they balance the importance given to each of the four evaluation criterions.

– *comp* denotes the completeness of the *Why*' field

$$\text{comp} = \frac{m}{5}, m \text{ the number of 4W1H questions answered by the } \text{Why}' \text{ field.}$$

– *diver* refers to the diversity of the what instances

375 $\text{diver} = \frac{n}{I}$, n is the number of what instances linking the *Why*' field to the event and I is the total number of what instances

– *conf* is the average confidence scores of the alignments that were used to build the *Why*' field (Section 3.3.2)

$$\text{conf} = \frac{1}{p} \sum_{i=1}^p c_i, c_i \text{ is the confidence score of the } i\text{th alignment.}$$

380 – *prox* denotes the spatio-temporal proximity the *Why*' field to the event triggering time and location.

$$\text{prox}(i_{\text{where}}, i_{\text{when}}) = \begin{cases} 0 & \text{if } i_{\text{when}} < \text{event}.t \\ 0.25 & \text{if } i_{\text{when}} \text{ and } i_{\text{where}} \text{ are empty} \\ 0.75 & \text{if } i_{\text{when}} < \text{event}.t \text{ and } i_{\text{where}} \text{ is empty} \\ 1 & \text{if } i_{\text{where}} = \text{event}.l \text{ and } i_{\text{when}} < \text{event}.t \end{cases}$$

i_{where} and i_{when} are the *When* and *Where* instances of the *Why*' field, $\text{event}.t$ and $\text{event}.l$ are event triggering time and location respectively.

Algorithm 4 ISEE tuples scoring

input: $ResultStep3 \leftarrow$ the Why' class Instances from Algorithm 3

$event \leftarrow$ the triggered event

```
1 WhyInstances  $\leftarrow$  GetWhyInstances(Result_step3)
2 for each  $i_{why}$  in WhyInstances do
3   |  $i_{why}.Scores \leftarrow$  GetScore(event,  $i_{why}$ )
4 end
```

385 4. EXPERIMENTAL RESULT

In this section, we present the results of a small and large scale experiments. In order to validate the genericity of the framework, the two experiments were conducted in two different application domains. The small scale experiment considers the example of a smart car park, while the large scale experiment deals with the example of a large office building. The main purpose of the small-scale experiment is to carry out quantitative and qualitative assessments of the semantic interconnections between the sensor network and the document corpus data. Thus, validate the effectiveness of our ISEE framework performance. The large-scale experiment aims to measure the impact of the choice of the alignment method (ontology matching, Figure 2) on the following steps of the framework. It also measures the completeness of the returned results in order to prove that ISEE framework can provide the user with a first guide to explain events within connected environments.

4.1. Small-scale experiment

This first experiment focuses on the example of a high CO2 event in a smart connected car park. First, we present document corpus and sensor network data sets. Then, we detail the experimentation procedure and present the obtained results.

400 4.1.1. Connected environment data

Document Corpus: we hand-picked 35 technical data sheets: 20 car technical data sheets and 15 others for different environment equipment systems (e.g., ventilation system, air conditioning system, lighting system, etc.). We used two ontologies: the building ontology *SAREF4BLDG* [17] and *The Automotive Ontology* [18]. We added in the building ontology the classes and properties which allow us to reference objects in the environment with respect to time and location. The automotive ontology already contained all the entities we needed, therefore, we did not apply any

changes. To instantiate the two ontologies, we used the collected document corpus. We developed a first python-based prototype of the ISEE framework. We used the RDFLib² python library and domain ontologies to annotate textual documents. Then, the annotations were parsed to build RDF
410 triples. Finally, RDF triples were introduced as new instances into domain ontologies. According to this domain-specific ontology instantiation process, the prototype generated an average of 652 RDF triplets per document.

Sensor Network data: to model the sensor network, we used the HSSN ontology [4]. We extended HSSN with the notion of events by adding the classes and properties related to the proposed
415 event definition syntax (Definition 3.1). Then, we instantiated the ontology and integrated a set of 78 sensors related to smart car parks as described in Section 3 (8 CO2 sensors, 8 humidity sensors, 8 temperature 450 sensors, 40 vehicle presence detectors, 8 smoke detectors and 6 surveillance cameras). Sensor data was simulated automatically³ using the BLE library module of the nRF5 SDK v11.0.0 API. To import the spreadsheet data into Protege, we used the plugin Cellfie⁴.

4.1.2. Evaluation results

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In what follows, we detail the quantitative and the qualitative evaluation results, respectively.

- **Qualitative Evaluation**

To assess the framework’s ability to build semantic interconnections between the two data sources, we summarized in Table 1 the total number of semantic links generated for each step. For this
425 first experiment, we set α, β, δ and γ to 1/4, respectively. The result of Step 1 of the ISEE process (Figure 6, and Algorithm 2) is described in the second column of Table 1. The first knowledge filtering stage reduces the knowledge repository to a total of 19 concepts (6 related to the event through a *What* connection and 13 related to the event through a *Who* connection). These 19 concepts in turn link 113 *What* and *Who* candidate instances as well as a huge number of When
430 and Where candidate instances within the HSSN, automotive, and building ontologies. Then, the result of Step 2 of the ISEE process (Figure 7, and Algorithm 3) is described in the third column of Table 1. This second knowledge filtering stage reduces the knowledge repository to a total of 44 instances (related to the event through different semantic connections).

²Available at: <https://pypi.org/project/rdflib/>

³Simulated data is available at <https://github.com/nabila2016/High-CO2-event.git>

⁴Available at <https://github.com/protegeproject/cellfie-plugin>

We can see that the number of instances potentially linked to the event decreased from 113 in Step 1 to 44 in Step 2, while the number of ISEE tuples increases from 6 in Step 1 to 11 tuples in Step 2. Besides, the importance of urgency level can also be seen here. Indeed, the filtering process from step 1 to step 2 requires a significant processing time which justifies the need of different urgency level. Finally, Step 3 (Algorithm 4) parses 44 semantic connections between the event and the related instances to score the ISEE tuples (Section 3.4.3, column 4 of Table 1). The top five ranked tuples consist of four car instances and one instance of a ventilation system. The four cars are highly polluting (a high average level of CO2 emissions), while the ventilator has been the subject of several technical maintenance during the last two months.

To sum up, Table 1 demonstrates that the ISEE framework actually builds semantic interconnections between sensor network and document collection data. It also shows the importance of urgency level.

Fields	Step 1	Step 2	Step 3
Urgency level	Medium	Low	Low
What concepts	6	6	-
Who concepts	13	13	-
What instances	50	13	-
Who instances	63	11	-
Where instances	-	10	-
When instances	-	10	-
ISEE tuples	6	11	11
Total	19 concepts 113 instances	19 concepts 44 instances 11 ISEE tuples	11 ranked ISEE tuples

Table 1: The ISEE links computed in steps 1, 2 and 3

445

• Quantitative Evaluation

We evaluated the relevance of the built ISEE interconnections throughout the following metrics: **Precision (P)**, **Recall (R)** and **F1-score** for Steps 1 and 2, and **Precision@n (P@n)** for Step 3, as Step 3 returns a ranked list. Besides, we mainly focused on What, Who, and Why candidate’s evaluation, since these are the parts that require the most complex processing in our

450

Fields	Step 1		Step 2	
	What concepts	Who concepts	What instances	Who instances
P	0.66	0.92	0.76	1
R	0.83	0.92	0.81	0.84
F1-score	0.73	0.92	0.78	0.91

Table 2: Evaluation of Steps 1 and 2 of ISEE framework based on the three evaluation metrics Precision, Recall and F1-score

ISEE Framework. Ground truth was built manually by experts. Evaluation results are shown in Table 2 (Step 1 and 2) and Table 3 (Step 3). In Step 1 (Table 2), the precision and recall are almost the same, since the number and the relevance of selected concepts depends directly on the semantic similarity measure (e.g., LowEmissionsCO2 concept is a false positive that was identified as a *Who* candidate since 'CO2 and 'EmissionsCO2' concepts are semantically close). In Step 2 (Table 2), the F1-score has improved, this is due to the fact that *What* and *Who* instances are selected according to the exact event triggering data (i.e., list of sensors, time and location), which allows, in most cases, to select the correct candidates. However, instances of the relevant concepts that were not selected in Step 1 are ignored by the selection process. Besides, although the car instance '2018_Hyundai_H1_II.Cargo' has a high CO2 emission level, it was not identified as a *Who* candidate, since it left the block C two minutes before event triggering. An improvement of the filtering process according to the type of event could therefore enhance the quality of instances selection process in Step 2. In Step 3 (Table 3), we noticed that the P@n decreases when the value of the n increases. This is due to the fact that a few ISEE tuples have been misclassified, this suggests that the score calculation formula (Section 3.4.3) must be improved, notably by adding additional classification criteria.

To sum up, this first experiment had two main objectives: (1) to show that ISEE Framework is able to interconnect sensor network and document collection data. This was demonstrated through the 4W1H connections built between domain ontologies in steps 1 and 2 (Columns 2 and 3 in Table 1); (ii) to demonstrate that the proposed filtering process is actually able to build relevant interpretations. This was also proved through the evaluation of ISEE tuples (Table 3).

P@n	P@3	P@5	p@8
Step 3 ISEE tuples	1	0.8	0.75

Table 3: Evaluation of Step 3 of ISEE framework based on Precision@n metric

4.2. Large-scale experiment

To further examine how effective our proposal is in practice, and how the choice of the alignment algorithm (ontology matching, domain-knowledge integration process in Figure 2) can impact its performance (Step 3, ISEE process in Figure 2), we apply it to a real-world data set [19]. This large-scale experiment focuses on the explanation of the aforementioned example of light wastage event (Section 2) in a large office building on a university campus. This smart building consists of four floors and a total of 53 rooms equipped with several types of sensors. In the following, we detail the procedure for instantiating domain ontologies based on this data set (Section 4.2.1). Then, we detail the proposed evaluation metrics in Section 4.2.2. Finally, Section 4.2.3 presents the evaluation results.

4.2.1. Connected environment data

Document Corpus: we used two domain ontologies to model document corpus data, the smart building ontology SAREF4BLDG [17] and the human resource ontology EOSK [20]. We hand-picked 150 technical data sheets (e.g., data sheets for lamps, laptops, projectors, ventilation system, badge access system, etc.)⁵ to instantiate the smart building ontology following the same procedure of the first experiment. In order to instantiate the human resource ontology EOSK, we used the API *Fake Name Generator*⁶ which randomly generates employee record text files. Then, we assigned to each of the 80 employee instances, an office as well as entry and exit times.

Sensor Network data: to model the sensor network, we used the HSSN ontology [4]. The data set [16] contains data collected from 204 sensors deployed in 51 rooms on 4 different floors. Each room is instrumented with 5 different types of sensors: a CO2 sensor, a temperature sensor, a humidity sensor, a light sensor and a motion detection sensor. The data from each

⁵The majority of these data sheets were collected from the two websites Amazon and Cdiscount.

⁶Available at <https://namefake.com/api>

495 sensor is recorded every 15 minutes and the data set contains one-week worth of data. Similar to the small scale experiment, to import the spreadsheet data into Protege we used the plugin Cellfie. A total of 30,584,853 observations were added into the ontology.

4.2.2. Evaluation metrics

In this section, we detail two evaluation metrics: an evaluation metric of the alignment technique that highlights the important aspects of the alignment in our context (ontology matching, domain-
500 knowledge integration process in Figure 2) and an evaluation metric of the explanation completeness (step 3, ISEE process in Figure 2).

The alignment technique evaluation

The alignment technique (ontology matching, domain-knowledge integration process in Figure
505 2) constitutes the cornerstone of our proposal and the basis of the following steps of ISEE framework (steps 1, 2, and 3 of ISEE process in Figure 2). Various existing alignment tools can be integrated in the ISEE process. The correctness of the ISEE final explanation depends directly on that of the initial alignment. If the number or quality of this alignment is not satisfactory, the framework may malfunction or return erroneous results. Consequently, we
510 propose a metric to evaluate the alignment method. This metric is based on three evaluation criteria, namely the connectivity of correspondences, their number and confidence score. We propose the following scoring formula:

$$\text{Score}_{\text{alignment}} = \frac{1}{\alpha + \beta + \gamma} (\alpha \cdot \text{Con} + \beta \cdot \text{Num} + \gamma \cdot \text{Conf})$$

- α, β and γ are weighting coefficients
- *Con* denotes the connectivity score of the alignment method, it assesses the ability of
515 the alignment technique to interconnect the maximum number of ontologies

$$\text{Con} = \frac{\text{Number of aligned ontologies}}{\text{Total number of ontologies}}$$
- *Num* the proportion of the aligned concepts

$$\text{Num} = \frac{\text{Number of aligned concepts}}{\text{Total number of concepts}}$$
- *Conf* denotes the mean of correspondence confidence scores
520

$$\text{Conf} = \frac{1}{n} \sum_{i=1}^n c_i, n \text{ is the total number of correspondences and } c_i \text{ the confidence score of the } i\text{th correspondence.}$$

For this experiment, we set the weighting coefficients to 0.33.

The Completeness evaluation

This metric assesses the completeness of the explanation returned to the user. As the What, Who, When, Where and How fields are built using the event triggering data (Definition 3.4), the completeness assessment considers the *Why* and *Why'* fields (steps 2 and 3, ISEE process Figure 2).

$$Comp = \frac{\alpha C_{what} + \beta C_{who} + \gamma C_{when} + \delta C_{where} + \theta C_{how}}{\alpha + \beta + \gamma + \delta + \theta}$$

- 525 – $\alpha, \beta, \gamma, \delta,$ and θ are weighting coefficients
- $C_{what}, C_{who}, C_{when}, C_{where},$ and C_{how} refer respectively to the completeness of the fields $m_{what}, m_{who}, m_{when}, m_{where},$ and m_{how} if the level of explanation required is medium or $f_{what}, f_{who}, f_{when}, f_{where},$ and f_{how} if it's high. The completeness of a field is equal to 1 if it is provided in the explanation and 0 if it is not.

530 4.2.3. Evaluation results

As stated earlier, the purpose of this large-scale experiment is to evaluate the impact of the alignment algorithm on the performance of the ISEE framework as well as the completeness of the built explanations. In order to match domain ontologies (i.e., HSSN, SAREF4BLDG and EOSK), we chose three different alignment tools which are widely used in the literature: *The Alignment*
 535 *API*[21], *AgreementMakerLight*[22], and *BLOOMS*[23]. Table 4 presents the alignment tools evaluation and the corresponding completeness scores. Columns 2, 3 and 4 correspond respectively to the three components *Con*, *Num* and *Conf* of the alignment evaluation metric (Section 4.2.2). The "score" column calculates the score of the alignment tools. The columns "Why Concepts" and "Why' instances" are respectively the total number of *Why* concept and *Why'* instance connections.
 540 The column "ISEE tuples" refers to the number of ISEE tuples. Finally, the column "ISEE tuples Completeness" computes the average completeness score of the ISEE tuples.

As you can see in the third column of Table 4, the number of the built correspondences differs according to the alignment algorithm as each one uses different techniques [16] (structural, terminological, etc.). *The alignment API* and *BLOOMS* produce similar correspondences (the same
 545 concepts are aligned by both alignment tools). This may be explained by the fact that both use

Alignment tools	Alignment evaluation				Completeness evaluation			
	Con	Num	Conf	Score	Why Concepts	Why' instances	ISEE tuples	ISEE tuples completeness
The Alignment API	3/3	29/242	0.74	0.61	18	23	7	0.88
Agreement-MakerLight	2/3	18/242	0.75	0.49	8	13	3	1
BLOOMS	3/3	28/242	0.78	0.63	18	23	7	0.88

Table 4: Evaluation of the alignment algorithms and the completeness

an external resource based alignment technique (i.e., Wordnet and Wikipedia respectively)⁷. In the "score" column of Table 4, we compute the alignment algorithm scores based on the metric presented in Section 4.2.2. The following three columns (i.e., 6, 7 and 8), show that the number of alignments built by the alignment algorithms has a direct impact on the number of connections build in the following steps. This impact continues until the final result is obtained (i.e., the total number of ISEE tuples). This can be explained by the fact that the ISEE steps are based on each other. Thus, a poor result in one step affects the following steps. The number of 4W connections built by the two alignment tools *The Alignment API* and *BLOOMS* is not so much impacted by the difference in the number of alignments produced by the latter. This is surely due to the fact that in the example of *light wastage event*, the concepts that have not been aligned are not necessary for the construction of the explanation. The 3 tuples returned by AgreementMakerLight are contained in the 7 tuples returned by the two other alignment tools (i.e., The Alignment API, BLOOMS). Besides, these 3 tuples do not contain the tuple best ranked by the expert. This proves that the more concepts are aligned, the more the ISEE framework is able to build different explanation tuples and find the most relevant ones. The ISEE tuples returned by The Alignment API and BLOOMS were almost similarly classified (only one ISEE tuple was classified differently). This is due to the fact that the score calculation formula (Section 3.4.3) has two criteria related to the ontology alignment:

⁷Note that *The alignment API* allows the use of several alignment techniques. For this experiment we choose a Wordnet based alignment technique.

diver which refers to the diversity of the what instances and *conf* which is the average confidence scores of the alignment. For the *diver* criterion, both The Alignment API and BLOOMS returned
565 almost the same alignment which means that the *diver* value is the same for both tools. For the *conf* criterion different value was returned by the tools. However, this had little influence on the final score. The most relevant tuple (choose by the expert) was returned in the first position by both tools. The column "ISEE tuples completeness" calculates the completeness of the resulting explanations. The results are positive and demonstrate that the ISEE process is able to construct
570 explanations correctly even if the number of aligned concepts is not so large. We do not see here the impact of the number of the built alignments on the average completeness score. This is because the three alignment algorithms produce a fairly close total number of alignments. Moreover, the average completeness does not favour the number of tuples but rather the completeness of each of these tuples.

575 To summarize this second experiment demonstrated that the choice of the alignment algorithm is important and strongly affects the performance of the framework, in particular the number of explanations returned to the user. The completeness score showed that the ISEE process is able to provide a complete explanation to the user even in a large scale dataset. Finally, for this experiment, both The Alignment API and BLOOMS gave good results. Hence, we chose 0.6 as the Threshold
580 for the alignment tool evaluation. This threshold will be further validated in our future work.

5. RELATED WORK

This section is organised in two parts. First, we present works on event explainability for connected environments and more generally sensor network data explainability. Then, we present works on event explainability for document collections.

585 First, concerning connected environments, major research proposals aim at event detection (e.g., detection of energy wastes in smart buildings, traffic monitoring and accident detection, detection of machine malfunctions) [4, 24]. There are less research works that go further and propose event explanation services. We can mention two categories of approaches. The first one focuses on video sources (e.g., camera) to explain events. It involves machine learning models associated
590 with enrichment techniques from the semantic web. The three frameworks detailed in [25, 26, 27] are dedicated to video data. The second one deals with works on heterogeneous sources (e.g., temperature sensor, humidity sensor, camera) to interpret events. It involves logic programming

and inference techniques associated with enrichment techniques from the semantic web to deduce semantic explanations of events. In [28, 29], authors detail two frameworks for events explanation
595 based on heterogeneous sensor data.

In this second part, we focus on works concerning event explainability within document collections. We pointed out three domains of work that deal with events in documents: sentiment variation, genes mutation and 5W1H question-answering. The first one concerns the explainability of sentiment variation on Twitter. It involves Latent Dirichlet Allocation (LDA) based models used
600 along with NLP techniques to automatically extract changing sentiments and topics (described in semantic graphs) within a period of time. The authors in [30, 31] propose two frameworks dedicated to sentiment variation analysis. The second domain concerns the explainability of genes mutation within biomedical scientific papers. It involves meta-knowledge schemes associated with text mining techniques. In [32], the authors detail a framework dedicated to genes mutation explainability.
605 The latter domain deals with 5W1H question-answering within online news articles (i.e., “who did what, when, where, how and why?”). It involves a wide range of NLP, machine learning and clustering techniques associated with reasoning methods on domain specific knowledge. The four frameworks detailed in [3, 6, 33, 34], are dedicated to 5W1H question-answering. Table 5 compares the aforementioned event explanation tools with ISEE framework according to the used data sources
610 (Columns 2-3), data types (Column 4) and the questions the approach answers (Columns 5-10). As you can see, event interpretation tools in the literature are dedicated either to sensor network or to a specific type of document corpus (e.g., tweets, online news). None of the proposed tools consider both of them. Moreover, the majority of research work that propose a full explanation (which answers the six questions of 5W1H) are those that deals with document corpus data. The
615 tools that consider only sensor network data do not give a full explanation. This demonstrate the importance of the information that document corpus data provides.

To summarize, event explainability or more generally information retrieval on sensor networks and document corpus data have been always considered as two distinct areas of research. In this paper, we showed that breaking down the walls between these two heterogeneous data sources, can
620 have a huge added value for the users of smart connected environments. We used the 5W1H model to bridge this gap and lead the interconnection process of these heterogeneous data sources.

Tools	Data sources		Data types	5W1H question answering					
	IoT	Corpus		What	Who	When	Where	How	Why
[30, 31, 33]		✓	Text (news)	✓	✓	✓	✓		✓
[3, 35, 34]		✓	Text (tweets)	✓	✓	✓	✓	✓	✓
[20, 25, 27]	✓		Video	✓	✓	✓	✓		
[28, 29]	✓		Any	✓	✓	✓	✓		
ISEE	✓	✓	Any	✓	✓	✓	✓	✓	✓

Table 5: Comparison of event explanation tools

6. CONCLUSION

Event explainability is the core concern of the work presented in this paper. Regarding information systems in connected environments, the combination of sensor network and document corpus data is essential since document corpus provide significant amounts of important and valuable information (e.g., technical data sheets, maintenance reports, customer sheets). Actually, connected environments do not support any connection between sensor network and document corpus data. Hence, a user has to look for an event explanation by himself through multiple queries on both data sources which is indeed very tedious, time consuming and requires a huge compilation effort.

For all those reasons, we proposed the ISEE framework, dedicated to event explainability in connected environments. ISEE is based on both (i) sensor network and document corpus data, and (ii) specific domain ontologies in order to link semantically such heterogeneous data. ISEE process consists of three steps. Based on the event definition data, the first step builds *What* and *Who* links between the event and related concepts of the specific domain ontologies. The second one, based on the event triggering data, builds *What*, *Who*, *When*, and *Where* links between the event and related instances of the specific domain ontologies. Those two previous steps aim at filtering iteratively concepts and instances of the domain ontologies. This approach makes it possible to reduce computations for different urgency levels since a first filtering reduces the ontologies to only the concepts semantically linked to the event definition data, then a second filtering reduces the ontologies to a few instances of these concepts semantically linked to the event triggering data. Finally, the last step, based on all the semantic links built previously, creates in turn different weighted instances of *Why* explanations named *ISEE tuples*. To sum up, 4 algorithms respectively support each of the steps of the event explanation process. These algorithms are based on formal

definitions of the ISEE environment. In addition, an ISEE model formally describes an event
645 explanation. A first experiment demonstrates that the ISEE process works and so could be very
helpful for one end-user to easily and simply interpret an event triggered in his environment. No
need any more to parse manually a huge amount of sensor and documentary data.

In terms of prospects, we are considering as a priority to test the ISEE process on different types
of events in order to make further improvements necessary for the scale-up and validate the align-
650 ment tool evaluation threshold. In addition, various scenarios remain to be studied. For example,
when several events are triggered at the same time, should we consider each event independently
and then look for possible interactions between them? Another case to be studied is that of compos-
ite events, i.e., an event composed of several events. When a composite event is triggered, should
we adapt the proposed ISEE algorithms to better explain this composite event? We will address
655 all these issues in future works.

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