High-Level Context Inference for Human Behavior Identification

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Abstract. This work presents the Mining Minds Context Ontology, an ontology for the identification of human behavior. This ontology comprehensively models high-level context based on low-level information, including the user activities, locations, and emotions. The Mining Minds Context Ontology is the means to infer high-level context from the low-level information. High-level contexts can be inferred from unclassified contexts by reasoning on the Mining Minds Context Ontology. The Mining Minds Context Ontology is shown to be flexible enough to operate in real life scenarios in which emotion recognition systems may not always be available. Furthermore, it is demonstrated that the activity and the location might not be enough to detect some of the high-level contexts, and that the emotion enables a more accurate high-level context identification. This work paves the path for the future implementation of the high-level context recognition system in the Mining Minds project.

Keywords: Context Recognition, Context Inference, Ontology, Ontological Reasoning, Human Behavior Identification

1 Introduction

The automatic identification of human behavior has evoked an enormous interest in the last years. Diverse technologies have been investigated to perform human behavior identification. For example, some works employ the use of geolocalization systems to track the user position and derive behavioral patterns [12, 13]. Other studies build on video, audio or a combination of both modalities to recognize some primitive emotional states [10]. Video systems [17] and on-body sensors [7, 14] have predominantly been considered for the recognition of people physical activity. With the boom of the wearable and mobile technology, several commercial solutions are increasingly available at the reach of most consumers. Misfit Shine [2] or Jawbone Up[1] are examples of these systems, which primarily focus on the analysis of the user body motion to keep track of their physical activities.

Human behavior identification is a complex problem that requires the analysis of multiple factors. Likewise, it requires to approach the person observation from various perspectives, including physical, mental and social aspects. Accordingly, current domain-specific solutions are seen to be certainly insufficient to deal with the magnitude of this problem. Instead, more complete platforms combining diverse technologies to infer people lifestyle and provide more personalized services are required. In this direction, Mining Minds [5, 6], a novel digital framework for personalized health and wellness support, provides technologies to infer low-level and high-level person-centric information, mainly the user context and behavior, and their physical, mental and social state. This paper focuses on the Mining Minds Context Ontology, used in Mining Minds to help describing the human behavior and to infer high-level context from low-level information.

Prior work supports the use of ontologies in Mining Minds. Ontology-based modeling overcomes the limitations of other models in terms of flexibility, extensibility, generality, expressiveness, and automatic code generation [19]. Moreover, ontology-based models can benefit from ontology reasoning and are one of the most promising models that fulfill the requirements for modeling context information [3]. Thus, ontology-based models are nowadays one of the main approaches to model context. Many ontologies have been created in the last years in order to model the user's context; however, none of them covers all the aspects required in Mining Minds. The CoBrA-Ont ontology [8] extends the SOUPA (Standard Ontologies for Ubiquitous and Pervasive Applications) [9] and defines people, places, and activities. The CoDAMos ontology [16], defines the user, among other entities, and defines for the users their mood, their absolute or relative location and some environmental variables. The CONON (CONtext ONtology) [20] is an upper ontology which defines general concepts like location, activity, and person. The Pervasive Information Visualization Ontology (PiVOn) [11] defines in the user ontology, their location, identity, activity, and time. The mIO! ontology [15] defines, among others, an ontology for the user, and for the location. Finally, the human activity recognition ontology [18] models individuals and social activities: personal, physical, professional activities and postures.

The rest of the paper is organized as follows. Section 2 introduces the architecture for High Level Context Awareness in Mining Minds. Section 3 describes the Mining Minds Context Ontology, which models context in a comprehensive manner. Some examples of the context classes illustrate the different modeling principles. Section 4 presents the inference method for the identification the user's context based on the Mining Minds Context Ontology. Several examples of context instances illustrate the modeling principles and inference logic. Finally, main conclusions and future steps are presented in Section 5.

2 Mining Minds High Level Context Awareness

In Mining Minds, the core technologies devised for the inference and modeling of the user's context constitute the Information Curation Layer [4]. Low Level Context Awareness (LLCA) and High Level Context Awareness (HLCA) are the main components of this layer. LLCA converts into categories, such as physical activities, emotional states, locations and social patterns, the wide-spectrum of data obtained from the user interaction with the real and cyber-world. HLCA models and infers more abstract context representations based on the categories identified by LLCA. HLCA builds on the Mining Minds Context Ontology (Section 3) and applies ontological inference to identify the user's context (Section 4). HLCA (Fig. 1) consists of four main components: High-Level Context Builder, High-Level Context Reasoner, High-Level Context Notifier, and Context Ontology Manager. The High-Level Context Builder receives the low-level information - activities, emotions, and locations - identified by LLCA and generates the ontological concepts representing an unclassified context. The Low-level Context Mapper interprets the received low-level information and transforms it into the corresponding ontological concepts. The Low-level Context Synchronizer searches for concurrent low-level information. The Context Instantiator creates a new instance of an unclassified high-level context which links to the comprising low-level information. The unclassified context is served to the High-Level Context Reasoner for its verification and classification. The Context Verifier checks the semantic and syntactic consistency of the unclassified context. The Context Classifier classifies the unclassified context into one of the different high-level contexts by applying ontological inference. Once a new context has been identified, the High-Level Context Notifier makes it available to the other Mining Minds layers for the creation of personalized health and wellness services and recommendations. The Context Ontology Manager provides persistence of the Mining Minds Context Ontology and supports the easy access and storage of context information.

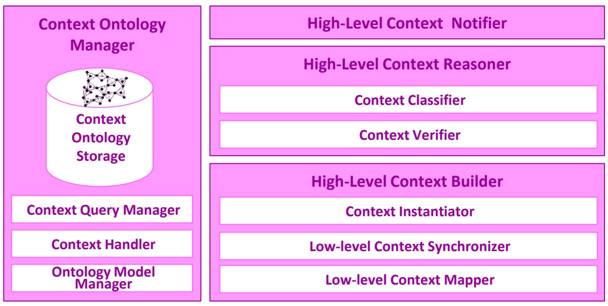

Fig. 1. Mining Minds High Level Context Awareness Architecture.

3 Mining Minds Context Ontology

The Mining Minds Context Ontology models high-level context in a comprehensive manner using the OWL2 ontology language. The ontology is available at `http://www.miningminds.re.kr/lifelog/context/context-v1.owl`.

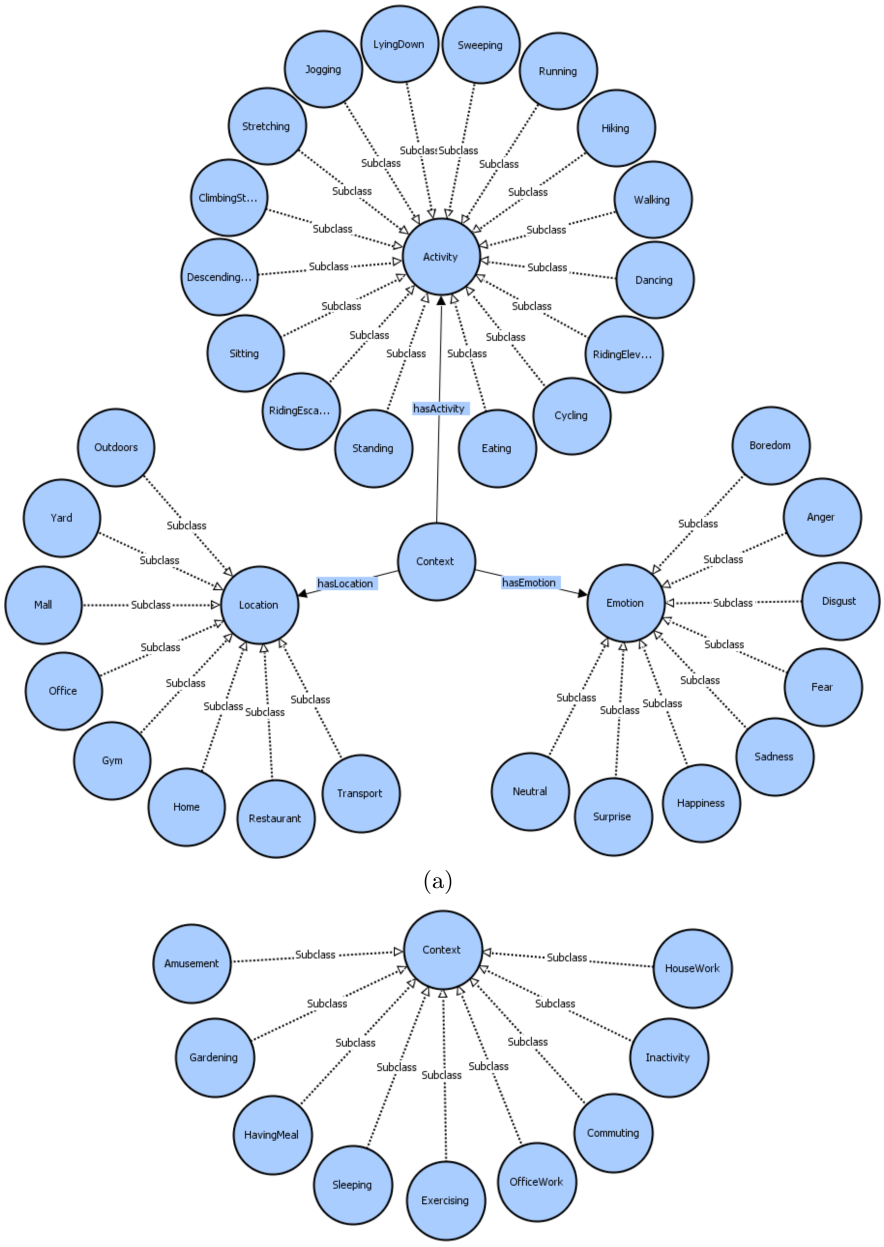

Fig. 2. Mining Minds Context Ontology: (a) `Context` class, `Activity`, `Location` and `Emotion` classes and subclasses, and `hasActivity`, `hasLocation` and `hasEmotion` properties; and (b) `Context` class and subclasses.

The main concept of this ontology is the `Context` class (Fig. 2), which defines the different high-level contexts. These contexts build on low-level information, including the recognized activities, detected locations, and recognized emotions. The `Activity`, the `Location`, and the `Emotion` classes have been described to model the different low-level information (Fig. 2(a)). These primitive classes are related to the `Context` class via the object properties `hasActivity`, `hasLocation` and `hasEmotion`. The `hasActivity` property has as domain the `Context` class and as range the `Activity` class. The `hasLocation` property has as domain the `Context` class and as range the `Location` class. The `hasEmotion` property has as domain the `Context` class and as range the `Emotion` class. The different recognized activities are modeled as 16 disjoint subclasses of the `Activity` class: `LyingDown`, `Sitting`, `Standing`, `Walking`, `Jogging`, `Running`, `Cycling`, `Hiking`, `Dancing`, `Stretching`, `Eating`, `Sweeping`, `ClimbingStairs`, `DescendingStairs`, `RidingElevator`, and `RidingEscalator`. The `Location` class has eight disjoint subclasses used to model the detected locations: `Home`, `Office`, `Restaurant`, `Gym`, `Mall`, `Transport`, `Yard`, and `Outdoors`. The recognized emotions are modeled through the eight disjoined subclasses of the `Emotion` class: `Happiness`, `Sadness`, `Anger`, `Disgust`, `Fear`, `Boredom`, `Surprise`, and `Neutral`.

The `Context` class has nine disjoint subclasses to define the different high-level contexts: `OfficeWork`, `Commuting`, `HouseWork`, `Gardening`, `HavingMeal`, `Amusement`, `Exercising`, `Sleeping`, and `Inactivity` (Fig. 2(b)). Each `Context` subclass is defined through complement classes and through existential and universal axioms that define the necessary and sufficient conditions of the equivalent anonymous class. How the equivalent anonymous classes for the nine `Context` subclasses have been described in Protégé is shown in Fig. 3. Three examples are extensively discussed in the following in order to illustrate the different modeling principles.

The `OfficeWork` class (Fig. 3(a)) is defined as being equivalent to the anonymous class: `Context and (hasActivity some Sitting) and (hasLocation some Office) and (hasActivity only Sitting) and (hasEmotion only (Anger or Boredom or Disgust or Happiness or Neutral)) and (hasLocation only Office)`. This means that to be a member of the defined class `OfficeWork`, an instance of the `Context` class must have a property of type `hasActivity` which relates to an instance of the `Sitting` class, and this property can only take as value an instance of the `Sitting` class. Moreover the instance of the `Context` class must also have a property of type `hasLocation` which relates to an instance of the `Office` class and only to an instance of the `Office` class. Finally, and in case the instance of the `Context` class has a property of type `hasEmotion`, this property must relate to an instance of the `Anger` class, the `Boredom` class, the `Disgust` class, the `Happiness` class, or the `Neutral` class. This universal restriction does not specify that the relationship through the `hasEmotion` property must exist, but that if it exists, it must be to the specified class members. Thus, if an instance of the `Context` class, fulfills the two existential and universal restrictions on the properties `hasActivity` and

```
Context
  and (hasActivity some Sitting)
  and (hasLocation some Office)
  and (hasActivity only Sitting)
  and (hasEmotion only
    (Anger or Boredom or Disgust or Happiness or Neutral))
  and (hasLocation only Office)
```

(a) OfficeWork

```
Context
  and (hasActivity some
    (Sitting or Standing))
  and (hasLocation some Transport)
  and (hasActivity only
    (Sitting or Standing))
  and (hasLocation only Transport)
```

(b) Commuting

```
Context
  and (hasActivity some
    (Standing or Sweeping or Walking))
  and (hasLocation some Home)
  and (hasActivity only
    (Standing or Sweeping or Walking))
  and (hasEmotion only
    (Anger or Boredom or Disgust or Happiness or Neutral))
  and (hasLocation only Home)
```

(c) HouseWork

```
Context
  and (hasActivity some
    (Standing or Sweeping or Walking))
  and (hasLocation some Yard)
  and (hasActivity only
    (Standing or Sweeping or Walking))
  and (hasEmotion only
    (Happiness or Neutral))
  and (hasLocation only Yard)
```

(d) Gardening

```
Context
  and (((hasActivity some Eating)
  and (hasLocation some
    (Home or Restaurant))
  and (hasActivity only Eating)
  and (hasLocation only
    (Home or Restaurant))) or ((hasActivity some Sitting)
  and (hasLocation some Restaurant)
  and (hasActivity only Sitting)
  and (hasLocation only Restaurant)))
  and (hasEmotion only
    (Disgust or Happiness or Neutral or Surprise))
```

(e) HavingMeal

```
Context
  and (hasActivity some
    (Dancing or Sitting or Standing or Walking))
  and (hasEmotion some Happiness)
  and (hasLocation some Mall)
  and (hasActivity only
    (Dancing or Sitting or Standing or Walking))
  and (hasEmotion only Happiness)
  and (hasLocation only Mall)
```

(f) Amusement

```
Context
  and (((hasActivity some Hiking)
  and (hasLocation some Outdoors)
  and (hasActivity only Hiking)
  and (hasLocation only Outdoors)) or ((hasActivity some Stretching)
  and (hasLocation some
    (Gym or Home or Office or Outdoors))
  and (hasActivity only Stretching)
  and (hasLocation only
    (Gym or Home or Office or Outdoors))) or ((hasActivity some
    (ClimbingStairs or DescendingStairs))
  and (hasLocation some
    (Gym or Home or Office))
  and (hasActivity only
    (ClimbingStairs or DescendingStairs))
  and (hasLocation only
    (Gym or Home or Office))) or ((hasActivity some
    (Cycling or Jogging or Running))
  and (hasLocation some
    (Gym or Outdoors))
  and (hasActivity only
    (Cycling or Jogging or Running))
  and (hasLocation only
    (Gym or Outdoors))))
  and (hasEmotion only
    (Happiness or Neutral))
```

(g) Exercising

```
Context
  and (hasActivity some LyingDown)
  and (hasLocation some Home)
  and (hasActivity only LyingDown)
  and (hasEmotion only Neutral)
  and (hasLocation only Home)
```

(h) Sleeping

```
Context
  and (not (Amusement or Commuting or Exercising or Gardening or HavingMeal or HouseWork or OfficeWork or Sleeping))
  and (hasActivity some
    (LyingDown or RidingElevator or RidingEscalator or Sitting or Standing))
  and (hasActivity only
    (LyingDown or RidingElevator or RidingEscalator or Sitting or Standing))
```

(i) Inactivity

Fig. 3. Mining Minds Context Ontology: Definition of the nine `Context` subclasses.

hasLocation, but does not asses a property of type hasEmotion, the instance will be inferred as being a member of the OfficeWork class.

The Amusement class (Fig. 3(f)) is defined as being equivalent to the anonymous class: Context and (hasActivity some (Dancing or Sitting or Standing or Walking)) and (hasEmotion some Happiness) and (hasLocation some Mall) and (hasActivity only (Dancing or Sitting or Standing or Walking)) and (hasEmotion only Happiness) and (hasLocation only Mall). This means that to be a member of the defined class Amusement, an instance of the Context class must have a property of type hasActivity which relates to an instance of the Dancing class, the Sitting class, the Standing class, or the Walking class, and this property can only take as value an instance of one of these four classes: Dancing, Sitting, Standing or Walking. Moreover the instance of the Context class must also have a property of type hasLocation which relates to an instance of the Mall class and only to an instance of the Mall class. Finally, the instance of the Context class must also have a property of type hasEmotion which relates to an instance of the Happiness class and only to an instance of the Happiness class. Summarizing, an instance of the Context class has to fulfill the described existential and universal restrictions on the properties hasActivity, hasLocation and hasEmotion in order to be inferred as a member of the Amusement class. Hence, the assertion of an instance of the Happiness class for the hasEmotion property is mandatory to infer the Amusement class. The type of the restrictions on the hasEmotion property is the main modeling difference between the Amusement class and the previously presented OfficeWork class. In the definition of Amusement class the hasEmotion property is mandatory due to existential and universal restrictions on this property, whereas in the definition of the OfficeWork class the hasEmotion property is optional since the restriction on this property is universal but not existential.

The Inactivity class (Fig. 3(i)) is defined as being equivalent to the anonymous class: Context and (not(Amusement or Commuting or Exercising or Gardening or HavingMeal or HouseWork or OfficeWork or Sleeping)) and (hasActivity some (LyingDown or RidingElevator or RidingEscalator or Sitting or Standing)) and (hasActivity only (LyingDown or RidingElevator or RidingEscalator or Sitting or Standing)). This means that to be a member of the defined class Inactivity, an instance of the Context class must not be an instance of any of the other subclasses of Context, i.e., it must not be an instance of the Amusement class, the Commuting class, the Exercising class, the Gardening class, the HavingMeal class, the HouseWork class, the OfficeWork class, or the Sleeping class. Moreover the instance of the Context class must also have a property of type hasActivity which relates to an instance of the LyingDown class, the RidingElevator class, the RidingEscalator class, the Sitting class, or the Standing class, and this property can only take as value an instance of one of these five classes: LyingDown, RidingElevator, RidingEscalator, Sitting, or Standing. In the modeling of the Inactivity class, not only existential and universal restrictions are used, but also the concept of complement class.

4 Context Inference in Mining Minds

The Mining Minds Context Ontology is the means to infer high-level context from low-level information. Using a reasoner, an instance of the `Context` class, i.e., an unclassified high-level context, can be determined to be a member of one of the nine `Context` subclasses: `OfficeWork`, `Commuting`, `HouseWork`, `Gardening`, `HavingMeal`, `Amusement`, `Exercising`, `Sleeping` and `Inactivity`. The instances of unclassified context are defined as individuals of the `Context` class for which their properties and types are asserted. The instances of the `Activity` class are asserted through the `hasActivity` property. The instances of the `Location` class are asserted through the `hasLocation` property. The instances of the `Emotion` class are asserted through the `hasEmotion` property. Reasoning in OWL is based on the Open World Assumption (OWA), which means that it cannot be assumed that something does not exist until it is explicitly stated that it does not exist. Therefore, type assertions are used as closure axioms to indicate that an individual does not exist for a property of the unclassified context individual. Fig. 4 shows several examples of instances of the `Context` class representing unclassified contexts and their inferred membership class computed using the HermiT reasoner in Protégé. In the following the examples are discussed in order to illustrate the modeling principles and the inference logic.

Fig. 4(a) shows an instance of the `Context` class for which the `hasActivity` property has been asserted to take the value `act_sitting`, and the `hasLocation` property has been asserted to take the value `loc_office`; where `act_sitting` is an instance of the `Sitting` class and `loc_office` is an instance of the `Office` class. Due to the OWA, the instance of the `Context` class has been asserted the type `hasActivity only ({act_sitting})` and the type `hasLocation only ({loc_office})`. These type assertions state that for this individual the `hasActivity` property only takes as value the instance `act_sitting`, and the `hasLocation` property only takes as value the instance `loc_office`. Furthermore, the `Context` instance has also been asserted the type `not (hasEmotion some Emotion)` in order to state that the individual does not have any property of type `hasEmotion` which takes any individual of the class `Emotion`. The reasoner is used to automatically classify this instance of the `Context` class. The instance complies with the `OfficeWork` class definition; therefore, it is classified as being a member of the `OfficeWork` class. Concretely, the `Context` instance fulfills the two existential and universal restrictions which state that the `hasActivity` relates to an instance of the `Sitting` class and only to an instance of the `Sitting` class, and `hasLocation` relates to an instance of the `Office` class and only to an instance of the `Office` class. Moreover, the universal restriction on the `hasEmotion` property does not state that the property must exist, as is the case in this instance; thus, the instance can be inferred as being a member of the `OfficeWork` class.

A similar `Context` instance is presented in Fig. 4(b); in addition to the property assertion for `hasActivity` and `hasLocation`, the `hasEmotion` property is asserted to take the value `emo_boredom`, which is an instance of the `Boredom` class. Furthermore, and in order to comply with the OWA, the corresponding

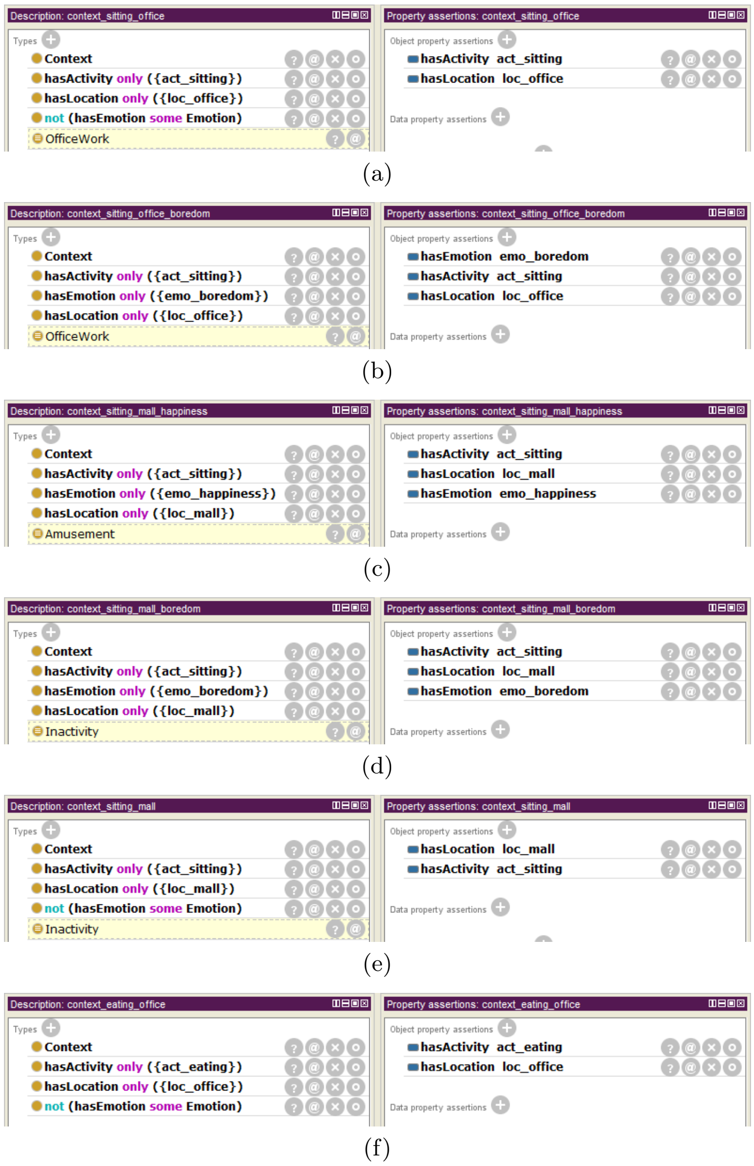

Fig. 4. Instances of the `Context` class which are classified as being members of the defined `Context` subclasses using the HermiT reasoner in Protégé. The inferred classes are highlighted in yellow: (a) `OfficeWork`, (b) `OfficeWork`, (c) `Amusement`, (d) `Inactivity`, (e) `Inactivity`, and (f) no class is inferred. `act_sitting` is an instance of the `Sitting` class, `act_eating` is an instance of the `Eating` class, `loc_office` is an instance of the `Office` class, `loc_mall` is an instance of the `Mall` class, `emo_boredom` is an instance of the `Boredom` class, and `emo_happiness` is an instance of the `Happiness` class.

type hasEmotion only ({emo_boredom}) is asserted for this Context instance. Not only does this instance comply with the existential and universal restrictions on the hasActivity property and the hasLocation property defined in the OfficeWork class definition, but also with the universal restriction on the hasEmotion property since the hasEmotion property exists and relates to an instance of the Boredom class. Thus, this Context instance is also classified by the reasoner as being a member of the OfficeWork class. The classification as members of the OfficeWork class of the two Context instances, one with an assertion on the hasEmotion property (Fig. 4(b)) and another one without it (Fig. 4(a)), proves the flexibility of the Mining Minds Context Ontology which enables the identification of high-level context even if one of the pieces of low-level information is missing. This is very helpful in real life scenarios where the emotion recognition systems are not always available and may produce detection events in a less regular basis than the activity recognizers or the location detectors.

Conversely, sometimes it is not possible to identify the high-level context if one of the low-level information is missing. Classifying Context instances which do not have asserted a hasEmotion property might be possible for some of the contexts like OfficeWork; however, this is not possible when the hasEmotion property is mandatory due to existential and universal restrictions defined on the Context subclass. This is the case of the Amusement class for which the assertion of an instance of the Happiness class for the hasEmotion property is required. The relevance of the hasEmotion property assertion can be observed for the Context instances presented in Fig. 4(c), Fig. 4(d) and Fig. 4(e). In these examples, only the Context instance in Fig. 4(c) is classified as being a member of the Amusement class since it is the only one for which the hasEmotion property is asserted to take as value an instance of the Happiness class, namely emo_happiness. The Context instance in Fig. 4(d) has asserted the hasEmotion property but this one takes as value emo_boredom which is an instance of the Boredom class and not an instance of the Happiness class; whereas the Context instance presented in Fig. 4(e) does not have a property of type hasEmotion. Therefore neither the Context instance in Fig. 4(d) nor the Context instance in Fig. 4(e) can be inferred as being members of the Amusement class. Even if a priori one could have expected the three Context instances being classified as the Amusement class, because for all three the hasActivity property has been asserted to take the value act_sitting, and the hasLocation property has been asserted to take the value loc_mall which is an instance of the Mall class, the different assertions of the hasEmotion property have proved the assumption to be wrong. This fact shows the relevance and influence on the high-level context of all low-level information types: activity, location and emotion. Moreover, this demonstrates that the activity and the location might not be enough to detect high-level context, and that the emotion enables a more accurate high-level context identification.

One should realize that the Context instance in Fig. 4(d) and the Context instance in Fig. 4(e) fulfill all the conditions to be inferred as being members of the `Inactivity` class, since they do not belong to any of the other subclasses of `Context` and they meet the restriction on the `hasActivity` property. Finally, some combinations of low-level information might not constitute a known high-level context. As an example, Fig. 4(f) shows a context instance which is not detected as any of the nine subclasses of `Context`.

5 Conclusions and Future Work

This study has introduced the Mining Minds Context Ontology, an ontology for the comprehensive and holistic identification of human behavior. The described ontology models high-level context based on low-level information, namely, activities, locations, and emotions. Conversely to other existing context ontologies for behavior recognition, the proposed model has demonstrated that activity and location information might not be enough to detect some of the high-level contexts, and that the emotion enables a more accurate high-level context identification. Moreover, the Mining Minds Context Ontology has been proved to be flexible enough to operate in real life scenarios in which emotion recognition systems may not always be available. Finally, it has also been shown that high-level contexts of diverse complexity can certainly be determined from the low-level information by reasoning on the Mining Minds Context Ontology. Next steps include the implementation of the proposed ontology and reasoning method to support online inference of unclassified context instances based on detected low-level information.

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