TALK: Tracking Activities by Linking Knowledge

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Abstract

Dependable and accurate monitoring of elderly at home becomes crucial to limit both the costs and human efforts of following up elderly for establishing a healthy care system. Human Activity Recognition (HAR) tools, based on sensors installed in smart homes, will become an important tool to provide useful information to the caregiver when something happens in the house of an elderly and care is required. The current available detection tools either exist out of interpretable knowledge-driven techniques or scalable data-driven ones. In this paper, a hybrid methodology that combines both approaches is designed and evaluated to Track Activities by Linking Knowledge (TALK). Both sensor data and their link to the relevant domain knowledge about where those sensors are installed, the performed activities that occur, and how the household is constructed, are generalised in a specific knowledge graph (KG) structure to represent continuous events. The interpretable knowledge graph embedding technique Instance Neighboring using Knowledge (INK) is then used to transform these events inside the KG to a tabular format, which can be used by any traditional machine learning classifier to create a HAR tool. The TALK methodology is evaluated on two HAR datasets and shows (a) that TALK outperforms both traditional automated data-driven as well as knowledge-driven techniques in terms of predictive performance, and (b) how TALK can be easily used in a more out of lab environment. All these results and the interpretable aspects show that TALK can become an important tool to monitor elderly in their homes efficiently, effectively and with less intrusive techniques.

Keywords: Human Activity Recognition (HAR), Hybrid Artificial Intelligence (AI), Knowledge Graph (KG) Embedding, Ambient Living, Smart Monitoring, eHealth

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1. Introduction

With the current ageing population, our care needs are shifting from acute to chronic care where people are living longer with one or more chronic diseases [1]. Such a chronic disease requires more complex care, requiring an estimated increase between 3.6% and 4.4% of elderly requiring beds in residential care centres by 2030 in Europe, Belgium [2].

To uphold the rather optimistic scenario of "only" 3.6% beds, care delivery should become more transmural and be facilitated at home and in service flats. By doing this, residential care can be reserved for those with severe care needs. Therefore, to maintain a sustainable healthcare model, the accessibility of homecare should increase from 5.8% of the european population to 8% in 2030 [2].

To facilitate this shift to homecare, dependable & accurate monitoring and follow-up of the elderly at home is crucial. Today, elderly are already increasingly equipped with Personal Alarm Systems (PAS) & monitoring devices (lifestyle monitoring, medical sensors, localization, etc.) [3]. These devices generate alarms that are forwarded to a call centre operator who is responsible for assessing the priority and context of the call and delegate it to appropriate caregivers. Whereas such generated alarms were previously efficiently handled in a hospital or nursing home due to direct access to the patient, they lead to a number of problems in the context of homecare, such as the inability to quickly assess the priority and validity of the alarms [4]. As such, precious time is often lost trying to reach the elderly. In the cases that the elderly can be contacted through e.g phone, they are often unable to communicate their situation clearly. Also false alarms, which account for more than one-third of the calls, cause a huge amount of lost time for caregivers [5].

As more and more households are equipped with smart Internet of Things (IoT) sensors, the context of what is happening when a personal alarm is generated can now be captured and analysed automatically to provide better care [6]. To deliver objective information to both the operator and caregiver when such an alarm is generated, the available monitoring devices in an ambient living setting can provide useful insights through Human Activity Recognition (HAR) models that help to analyse the sensor signals without the need of a nurse or operator.

More concrete, an operator could be alarmed that a resident needs some care. Based on the HAR results the operator could identify that certain daily routines, such as eating breakfast and showering were not performed. This information can already indicate more specialised care will be required and that, in this case, the chance of a false alarm will be rather low.

However, the currently available HAR models either focus on the data generated by the monitoring devices or use so-called domain knowledge to derive the human activity [7]. A combination of both data- and knowledge-driven techniques are rather sparse and are mostly limited by advanced rule-based systems [8]. Moreover those combined approaches rarely take into account all domain related knowledge, to incorporate information about the sensor placements, the different rooms inside the house or the possible human activities that can occur inside those rooms. Combining both the available knowledge about a household and monitoring device together with the generated data could not only be used to learn the detection of human activities, they could also provide more explainable results towards the nurse and operators and let them verify whether the predictions of such a model can be trusted.

In this work, we present such a combined HAR model to Track Activities by Linking Knowledge (TALK). The TALK methodology transforms all the gathered data in the context of a smart house together with the available domain knowledge into a Knowledge Graph (KG). The data is grouped into events, which represent nodes within our KG. On those event nodes, data observations from different devices are linked together with the additional knowledge of, e.g., where those devices are placed within the house and what they are actually measuring. The KG embedding technique Instancce Neighboring using Knowledge (INK) is then used to generate interpretable KG embeddings for each of these events. The result of INK is later fed to a Machine Learning (ML) classifier to predict the corresponding human activity associated with these events. An evaluation of TALK is performed based on the Data Analytics for Health and Connected Care (DAHCC) dataset[1], which contains gathered data of more than 5 different monitoring devices for 30 participants performing daily life activities in a home [9]. The obtained results show that the TALK methodology is indeed effective while still being interpretable. The contributions of the paper are therefore summarized as

[1] https://dahcc.idlab.ugent.be

follows:

- We design and present the TALK approach that combines time series events and activity meta information together in a unified KG, which is ideally suited as input for ML methods.

- We designed a novel activity recognition technique based on hybrid AI, which combines both raw sensor data with metadata about the environment in one unified and generic approach.

- We show that by using our own interpretable KG embedding technique INK in the hybrid AI method, an activity recognition technique can be achieved that is interpretable and can thus deliver insights on why a particular activity was recognized by the AI based on all input in the KG.

- Based on both our own Open Dataset, as well as an external benchmark dataset, we showcase that the presented hybrid AI method outperforms the state-of-the-art activity recognition algorithms, both in terms of prediction accuracy, as well as in terms of interpretability of the results.

The remainder of this paper is structured as follows: Section 2 provides an overview of the relevant HAR studies and how they relate to the problem discussed above. The description of the TALK methodology on this DAHCC dataset is described in Section 3. Section 4 describes the open DAHCC ontology and datasets on which TALK is evaluated. Section 5 described the evaluation and obtained results. These results are discussed in Section 6. At last, future work and a conclusion is provided in Section 7.

2. Related work

HAR algorithms and models for smart-home environments can be classified in the area of pattern recognition. Two broad fields of research exist in literature [10]: data-driven and knowledge-driven approaches. On the one hand, data-driven approaches rely on gathered data from sensors and actuators about the behavior of the users to create an Artificial Intelligence (AI) model to recognize human activity. On the other hand, expert knowledge and common-sense rules are used in the knowledge-driven field. They use prior knowledge, the modelling information of the domain and logical reasoning to infer human activity. The following two subsections further elaborate on the state-of-the-art within both fields and provide their advantages and drawbacks.

2.1. Data-driven HAR

Data-driven HAR models are differentiated between their generative and discriminative capabilities [11]. Generative models use probabilistic analysis models such as Markov models and Bayesian networks to define the activity input or data space. Such a generative model takes into account the inhabitant's preferences and tunes the models according to this information. The drawback of this approach is its rather static nature, non-evolving and tailored to the provided data. In contrast, the discriminative approach maps the obtained inputs to the activity outputs, usually provided as ground-truth labels by the users, e.g. by annotating activities or analysing video images of the user's activities. Machine Learning (ML) is such a discriminative approach in this field. Within ML, as well as in data-driven HAR, both supervised and unsupervised learning methods exist.

In previous research, decision trees [12], conditional random fields [13], support vector machines [14], naive bayes classifiers [15] and Multi-Layer Perceptrons [16] are used to detect and classify human activities. While some models outperform others, the specific use case setting or the difference in amount of gathered data to train the models make it difficult to define a clear winning prediction model for HAR.

All data-driven HAR model have the advantage of probabilistic modelling. It can handle uncertainty or provide a probabilistic outcome for all learned activities when a new observation or set of observations needs to be analysed [7]. Such ML models can also handle noisy, uncertain and incomplete data. To learn these models, no upfront domain knowledge is required.

The drawback of all these data-driven HAR techniques is that both the generative and discriminative approach requires a large amount of data. The need for data is also reflected in the cold-start problem of these methods. A large amount of data should be available upfront to learn and train the models before predictions can be made or adapted to a more personalised setting. In the case of a supervised training approach, even a large amount of clean and correctly labelled data is needed. Another problem with data-driven HAR approaches is that they are explicitly tailored to the given dataset and domain [17]. Therefore, new models and even new data collection campaigns are needed when HAR has to be performed in a new environment, with different sensors and with different activity labels.

Another drawback of this field is the less interpretable predictions generated by a data-driven model. Most of the time, an operator still has to correlate in many cases the sensor values and interpret the results to understand why a certain prediction was made.

2.2. Knowledge-driven HAR

Knowledge-driven HAR methods exploit the activity and sensor knowledge modelling and use logical reasoning to perform activity recognition. The general procedure of a knowledge-driven approach can be summarised in 3 steps [17]:

1. Explicitly define and describe all possible activities within the domain using a knowledge representation formalism.
2. Aggregate and transform the sensor data into logical, interpretable terms and formulas.
3. Perform logical reasoning to extract a minimal set of rules (models) which could explain the activities based on a set of observations.

The knowledge structure is modelled and represented through, e.g., schemes, rules, or networks. Knowledge-driven HAR is further divided in three subapproaches: mining knowledge from web resources, where textual descriptions of human activities are translated into concepts and actions that can be processed by an inference engine [18], logic-based approaches [19], and, the more recently adopted, ontology-based approaches. A well-known logic based HAR approach is finite automate or finite state machines [20]. In this technique, activities are defined as states and rules are constructed to go from one state to another. These state transitions depend upon the provided input symbols, such as discrete sensor values. Finite automata are especially tailored to a specific task and context. When the context of the task changes, a new automaton has to be designed by a human expert to make it adaptable to this new case. The ontology-based approaches do not depend on algorithmic choices and are, therefore, preferred over the other methods in the last decade. Hooda et al. [21] proposed a an overview of ontology-based HAR and also constructed sensor and activity ontologies for explicit domain modelling to infer human activities. Ontological representations use assertion axioms learned from data or defined by the user to make these inferences of the activities [22].

Knowledge-driven techniques have the advantages to represent and model the activities as most complete as possible to overcome the activity diversity and provide an explanation why a certain prediction was made. However, the limitations of these approaches are the complete domain knowledge requirements to build activities models and the weakness in handling uncertainty and adaptability to changes and new settings or activities [17]. They need domain experts to design knowledge and rules and new rules can break or bypass the previous rules.

2.3. The need for a hybrid approach

While both separate approaches have their shortcomings, both the knowledge-driven and data-driven HAR solution can also be combined to resolve multiple of the above-mentioned issues and obtain better, interpretable results.

First steps were already taken to incorporate data-driven learning capabilities into knowledge-driven approaches to address the aforementioned problems of activity modelling [17]. The process consists of three key phases. In the first phase the initial knowledge-driven models are created through ontological engineering by leveraging domain knowledge and heuristics. This solves the so-called cold-start when not enough data is available to create data-driven detectors. The ontological engineering method can now be applied on a small amount of data, and can be seen as a new automatic procedure to get more reliable labels for a data-driven model. The usage of user-feedback can help to correct and adapt faulty or missed predictions in this case. In the third phase, the classification results from the second phase are analysed to discover new activities and create data-driven HAR models. These new learnt activity patterns are in turn used to update and extend the knowledge-driven models. Once the first phase completes, the remaining two-phase process can iterate many rounds to incrementally evolve the models, leading to a complete, accurate and up-to-date HAR. While this form of a hybrid approach overcomes all shortcomings, it also implies multiple systems have to be designed to work together. This hybrid AI architecture has already been efficiently implemented in a predictive maintenance domain [23] and is translated to a HAR setting. In these HAR cases, either ontological activity concepts are used to fix inconsistencies in the outcome of a ML classifier [24] or a knowledge-driven reasoning step is performed to detect a first set of activities, which can later improve this initial knowledge-driven activity model [25]. Most of these techniques are dependent on the environmental context and in many cases, two or more models have to be maintained when applied in a real-time, streaming context.

The recent advances in knowledge engineering offers also the possibility for a new type of hybrid approach using a KG. Here, both the sensor data and contextual metadata are combined in one graph, which links the domain knowledge with the sensor or input observations. When all information is available, so-called KG embeddings can be used to transform the more graphical representation of all the data into a representation that can be used as input in a ML model [26, 27]. When the embedding procedure can be guaranteed to generate interpretable embeddings, the outcome of the generated models can also provide interpretable predictions. This combination of incorporating both the sensor data while providing interpretable results is crucial to let these HAR models operate in a healthcare setting. Techniques exist which can also take into account a KG as input [28, 29]. But to our knowledge, we are the first to evaluate and propose a hybrid approach for HAR, which takes a KG as input and is still able to provide interpretable results that have not been reported upon before. Here, less individual knowledge- and data-driven systems have to be designed and combined to generate a new solution.

3. TALK methodology

The TALK hybrid approach presented in this paper consists of 3 main steps. First, the sensor data, activity information and existing contextual information must be combined in one data structure. To link all this information together, a KG is being used, backed by an ontology to clearly define the relationship between the activities and the sensor data. Second, we create KG embeddings for those nodes of interest which hold activity information. At last, these node embeddings are fed to an ML classifier together with the corresponding labelled information to train and make activity predictions. An overview of this approach is visualised in Figure 1. This section further describes these three steps in detail.

3.1. TALK KG

The KG structure used within the TALK methodology had two requirements:

- Data and metadata should be linked together such that relevant information regarding a performed activity can be found in a limited number of hops.

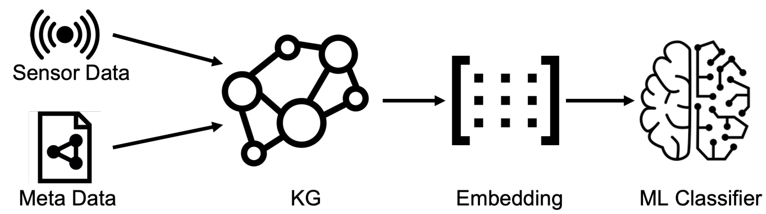

Figure 1: Overview of the TALK approach to create a Hybrid AI HAR detection tool.

- As activities have a temporal aspect, the KG should also keep such a temporal structure. It should be possible to hop from the current obtained information to the previously seen data.

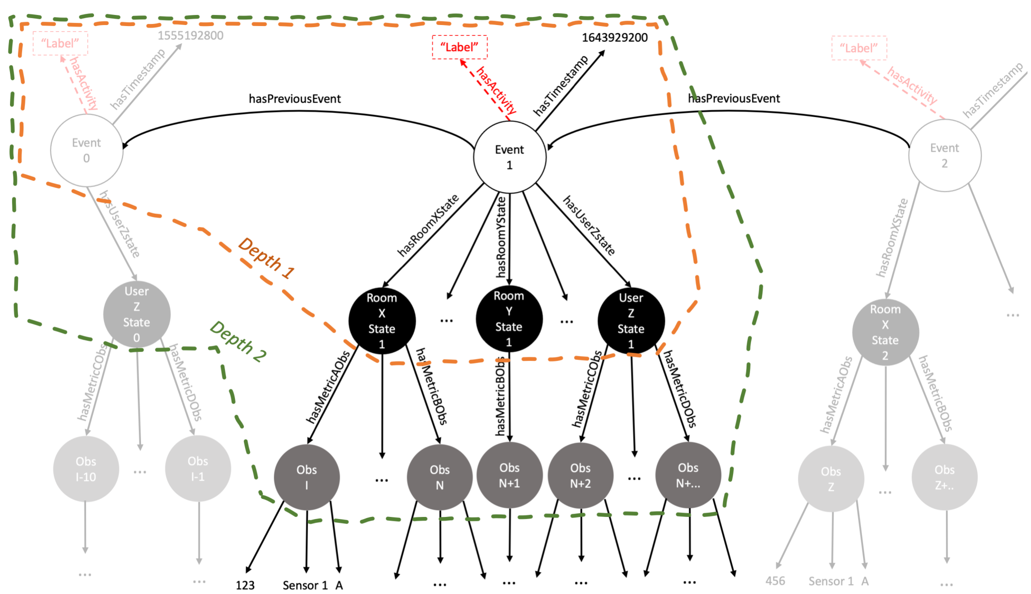

Figure 2: Representation of the KG within TALK. Sensor observations are linked to events using contextual state nodes. The event nodes are linked to each other using the "hasPreviousEvent" relationship. The neighborhood of the Event 1 node for depth 1 (orange) and depth 2 (green) is also highlighted in this Figure.

Figure 2 shows how the TALK KG is designed to meet those requirements. Event nodes are generated which aggregate observations for a certain amount of time (x seconds, x minutes, ... depending on the use case at hand). To this event node, observations can be linked. Instead of linking the observations directly to this event node, additional sub nodes are created to aggregate those observations related to the same concept together. Here, in the domain of lifestyle and activity detection, both the rooms inside the residents' house and the residents themselves can be in a certain state for a certain amount of time. The sensor observations in these rooms or the observations from the wearable devices attached to the resident are linked to these states when they occurred during the time this particular state was captured (e.g. when they occurred within the time range of the state). This link relationship is based on which sensor created the observation, together with the provided meta information of where this sensor is installed (e.g., which room, attached to which user etc.).

In a less abstract sense, the TALK approach will group the sensor observations based on both a certain time interval (state) and the location where this sensor originated from. One of these locations can be the body of the user (e.g. for wearable devices).

Events are also linked to each other using the "hasPreviousEvent" relationship to enable efficiently hopping to an event back in time. Events that belong to a certain performed activity can also incorporate the "hasActivity" label information.

3.2. TALK INK embedding

The KG combines efficiently both the data and metadata of a performed activity. Traditional ML models are unable to deal directly with graph-based input. As such, if such a ML model wants to detect activities based on this information automatically, the KG should be represented as a vector. A large amount of so-called KG embedding techniques exist, which transform the whole KG or particular nodes within a KG to such a vector representation [27], such as TransE and RDF2Vec. All those techniques however have the drawback of transforming the interpretable KG into uninterpretable embeddings, which result in predictions being made with a ML classifier which are hard to relate back to the originally provided information. Moreover, the transformation always leads to a loss of information. Techniques exist, i.e. graph neural networks, which directly take the KG as input and make use of Deep Learning (DL) to implicitly learn an embedding and simultaneously accomplish the classification task [30]. However, these techniques do not scale towards large graphs, and whenever the KG changes (e.g. new nodes or edges being added), a new model has to be trained. These techniques require a large amount of data to be trained properly. Therefore, we designed a novel embedding technique called INK [31], which is optimal for usage within TALK as INK embeds the KG in an interpretable 2D matrix and is not dependent upon the ML model that takes this 2D matrix as input. To generate such a 2D matrix, INK queries the neighborhood of a node of interest and transforms the information within this neighborhood into features. As an example, INK will embed the "Event 1" node in Figure 2 as follows. In a first step, INK gathers the neighborhood of this event node. A neighborhood of a certain node is defined by all the nodes that can be reached starting from the node of interest (here the "Event 1" node). To gather those nodes, INK traverses paths following the direction of the edges starting from the node of interest towards all nodes that can be reached. As this neighborhood can be very large, we usually limit the search depth by a parameter value. This neighborhood depth indicates the number of edges that can be taken starting from the node of interest towards the nodes within the neighborhood. In our example, a neighborhood depth of 1 will contain the nearby nodes of our "Event 1" node that can be reached following the connected outgoing relationship edges. This is shown in Figure 2, where the neighborhood of Event 1 at depth 1 is surrounded in orange. These are all the room and user state nodes, the timestamp, the activity label and the previous "Event 0" node.

After INK acquires the neighborhood of the node of interest, it transforms the relevant information in this neighborhood into a dictionary format. The dictionary key is defined by the edge relationship. The value is the list of nodes related to this relationship as a relationship can occur multiple times starting from a node of interest reaching different nodes (e.g. multiple room X states linked to an event node). In our example a hasRoomXState→[RoomXState1] key-value pair will be available in this dictionary, together with all other pairs found at neighborhood depth 1 as shown in Table 1. When creating these key-value pairs for a neighborhood depth larger than 1, INK concatenates the relationship edges together and neglects the intermediate nodes as this information is made available within our dictionary when creating key-value pairs at a lower depth. INK would create the following dictionary entry for a neighborhood depth 2: hasRoomXState.hasMetricAobs→[Obs1]. In our example Figure 2, the neighborhood depth 2 is visualized in green. One can see that a minimal depth parameter of 3 is required to capture the sensor observation values (3 edges have to be traversed to reach this sensor information). If the sensor values of the previous event are also of interest, a depth parameter value of

Table 1: Dictionary representation created by INK for the Event 1 node in Figure 2.

Key	Value
hasRoomXState	[RoomXState1]
hasRoomYState	[RoomYState1]
hasUserZState	[User2State1]
..	..
hasRoomXState.hasMetricAObs	[Obs1]
hasRoomXState.hasMetricBObs	[ObsN]
..	..

4 is required.

A neighborhood dictionary is made for every node that is of interest. In our example, INK would create this dictionary for every event node for which an activity label is provided. To transform all these dictionaries in a 2D matrix, we take as an index the according node of interest and create column features by the concatenation of the relationship key and the value in the list according to this key within the dictionary. Both the keys and a combination of keys and values are provided in this 2D matrix. The creation of the key-value combination is repeated for every value within the dictionary value list. An example of such a 2D Matrix for our example is provided in Table 2. In our example of the "Event 1" node, this specific event node is defined as an index entry, and hasRoomXState$RoomXState1 is a generated column feature from the "Event 1" dictionary. The "$" sign is used as concatenation character, and indicates where the relationship string ends. To indicate whether this feature can be found within our index node of interest, we provide a binary indicator in the according cell.

Table 2: Example of a depth 3 INK two dimensional representation for the three event nodes in example Figure 2. INK can both combine real values with binary indicators to indicate the relational information when available.

	hasRoomXState	hasRoomXState$RoomXState1	hasRoomXState.hasMetricAObs.hasValue	...	hasTimestamp
Event 0	0	0	Nan	...	Value
Event 1	1	1	123	...	Value
Event 2	1	0	456	...	Value

When more and more nodes of interest transform their dictionaries within this 2D matrix representation, the more similar information that can be found in these neighborhoods will be mapped on the same feature columns. This is visualized in Table 2 where an example 2D matrix representation is shown for the three event nodes in our example of Figure 2. The nodes “Event 1” and “Event 2” both have “hasRoomXState” information as shown in Figure 2 and the first column of Table 2 while the “Event 0” node doesn’t provide this information.

INK has the option to neglect certain relationships, such that this information is not being used during the creation of the INK embedding. In the context of HAR, the “hasActivity” relationship was neglected by INK such that the labeled information was not incorporated in the embedding itself as this would introduce a label leakage during the training and evaluation process of a ML classifier. INK also has the ability to avoid transforming numerical values into separated columns. In the third column of Table 2, we see for our example nodes that their raw sensor values are not transformed into separated binary column indicators, but that they are provided as is.

3.3. TALK classifier

The INK embedding can be seen as a traditional feature matrix, where for each event node, features are constructed which hold both sensor and contextual information. The HAR labels accompanied with these events can be queried from the original KG based on the event’s unique identifier. This combination of a feature set and an according label set can be provided to any supervised ML classifier.

4. DAHCC Ontology and Datasets

To provide a link between sensors and observations together with the human activities being predicted by an AI model, the Data Analytics for Health and Connected Care (DAHCC) ontology [9] is used to describe this.

The DAHCC ontology consists of 4 sub ontologies, ranging from human activities to sensor observations for both wearable and ambient living. These ontologies are based upon the SAREF standards to describe sensors and their observations, buildings and physical objects as well as how these concepts relate to health actors and patients. The DAHCC ontology also describes the concepts related to ML models based on the Execution-Executor-Procedure (EEP) ontology. An example of how the observation data of a sensor can be enriched with this ontology is shown in Figure 3. The data of a single sample is mapped to an observation node in our KG and this node is linked to the corresponding sensor responsible for generating such observations. The sensor itself analyses the state of a certain object, which is located at a certain location (in the example of Figure 3, a pressure sensor analyses the state of the bed, which is located in the bedroom. This bedroom can be located at a certain floor in a certain house). Similarly, we can define the user in our KG and define e.g. its indoor location.

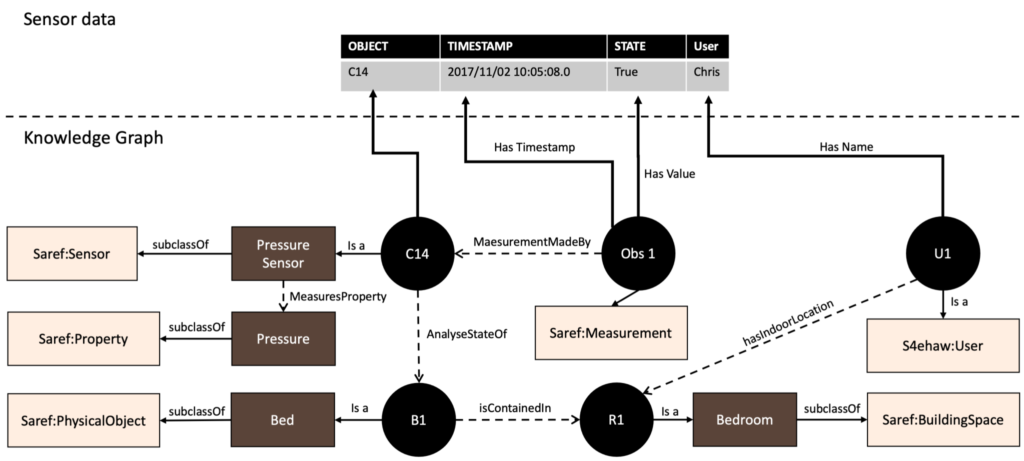

Figure 3: Semantic enrichment of a sensor observation using the DAHCC components. Additional domain knowledge about the use case can also be linked. In this example the sensor data of a pressure sensor, measuring the pressure of a bed inside a bedroom is being enriched. The user responsible for these sensor values is also mapped within this sub graph. Black round circles represent the instantiated nodes in our KG. All squared boxes represent ontological concepts either from the DAHCC ontology or from external ontologies).

The semantically enriched observation using the DAHCC ontology holds enough information to transform the data and metadata into the TALK KG as described in Section 3.

To evaluate the TALK methodology and to show the advantage of combining data and metadata together in one KG, we used two HAR life style datasets:

- UCAmI Cup dataset [32]: A HAR dataset to track activities of daily living generated in the UJAmI Smart Lab, University of Jaén. The dataset was chosen for the first edition of the UCAmI Cup and represents 246 activities performed over a period of ten days carried out by a single inhabitant. The dataset includes four data sources: (i) event streams from 30 binary sensors, (ii) intelligent floor location data, (iii) proximity data between a smart watch worn by the inhabitant and 15 Bluetooth Low Energy beacons, and (iv) acceleration of the smart watch. Activity labels were provided for every 30 seconds. An overview of this dataset is provided in Table 3. As this dataset was also part of a competition, a clear train-test split was also provided. The UCAmI Cup dataset was semantically enriched using the DAHCC concepts in order to evaluate the TALK methodology for this paper. This UCAmI TALK KG is also made available in our repository[2]

Table 3: Summary overview of UCAmI cup dataset.

Source	**Raw Data**	**Details**	**Description**
Acceleration	X, Y and Z axis	acceleration of inhabitant measured at 32hz	
Intelligent floor	Boolean contact	Indoor location tiles	Location is 2D space
Proximity	Object, RSSI	Book, TV controller, Door entrance, Medicine box, Cupboards, Fridge, Garbage can, Wardrobe, Drawer, Tap, Toothbrush, Laundry basket	Location of inhabitant near these objects
Binary Sensors	Object, State	Door open, TV, Motion sensors, Dishwasher, Drawer state, Water boiler, Microwave, Tap, Tank, Bed, Kitchen faucet, Sofa pressure	Usage of objects
Activity	Category + label	Shower, Brush Teeth, Use toilet, Get dressed, Take medicine, Dinner, Lunch, Breakfast, Take snack, Prepare breakfast, Prepare dinner, Prepare Lunch, Go home, Leave home, Visit lab, Sleep, Relax on sofa, Play videogame, Read book, Watch TV, Work at table, Do dishes, Put washing machine on, Take out trash, Throw waste in bin	Activities performed by a single user

- DAHCC dataset [9][3]: Ambient living situation where a lot of non-invasive sensors are installed on two floors at the HomeLab of imec. 30 different participants performed daily life activities and sensor data from various sources was captured. Participants were also equipped with smartphone and wearables to analyse their smartphone usage, indoor location and some biomedical parameters, e.g. skin conductance and heart rate variability. An overview of this dataset is given in Table 4. Together with this dataset, all metadata related to the imec HomeLab, the sensor installations and performed activities are semantically enriched using the DAHCC ontology. This DAHCC TALK KG is also made available in our repository[4]. Labelled activities were pro-

[2]`https://github.com/predict-idlab/TALK/tree/main/UCAmI`
[3]`https://dahcc.idlab.ugent.be/dataset.html`
[4]`https://github.com/predict-idlab/TALK/tree/main/DAHCC`

vided by the participant using a smartphone application. They indicated the start and stop times every time a human activity was performed. The average number of activities registered per participant is 70.7.

Table 4: Summary overview of DAHCC dataset.

Source	Raw Data	Details	Description
Wearable	X, Y and Z axis Acceleration X, Y and Z axis Gyroscope Blood Volume Pulse (BVP) Galvanic Skin Response (GSR) Skin temperature	Inhabitant specific parameters	Empatica E4 was used as wearable device
Netatmo	Various values within a specific room	Rooms: Kitchen, Master bedroom, Bathroom, Toilet	Room temperature, Room CO2, Room humidity, Room loudness
EnOcean	Object state	Door contact sensor, cabinet contact sensor	Measure open/close state of doors/drawers/cabinets
Steinel	People presence People count	Rooms: Living room, kitchen, hallways, master bedroom	Detects and counts the number of people within a certain room
Velbus	Various values within a specific room	Available in all rooms	Measures the energy consumption of each wall socket, the energy consumption of the major appliances, indoor temperature within a room, state of the windows, state of the blinds, state of the lights, state of the motion detectors
Aquara	Location	Proximity based indoor localisation detection	Indoor localisation system of Televicc Healthcare
Activity	Label	RoomTransition, Toileting, Organizing,Working, WashingHands,DrinkPreparation, WatchingTVActively, UsingMobilePhone, PreparingMeal,EatingMeal, GettingDressed, UsingComputer, BrushingTeeth, DoorWalkThrough, Sleeping, WakingUp,Serving, ObjectUse, SocialInteraction, GettingReadyToSleep, Walking,Drinking, Showering, ShavingBrushingHair, TakingMedication, SocialMedia, EatingSnack, PreparingSnacks, Dishwashing, Exercising, Wandering, Cleaning, Cosmetics	Activities performed by a 42 users

Although both datasets contain different sensors and different household layouts, the obtained TALK KGs are quite similar to each other. Both the DAHCC TALK KG and UCAmI Cup TALK KG describe observations related to the state of an appliance/physical object within a room or building space of the smart labs.

5. Evaluation and Results

For both semantically enriched datasets, INK embeddings were generated for all nodes containing an associated activity label. The labels were excluded from the KGs when creating the embeddings to avoid labelled information getting incorporated. For the UCAmI Cup dataset, event nodes were embedded for every 30 seconds, as the labelled information was originally provided for every 30 seconds. The DAHCC dataset didn't have activity labels being partitioned every x seconds. Therefore, events are created every 30 seconds, and we compare the activity begin and end timestamp to assign the corresponding label(s).

Only a single activity at a time was performed during the UCAmI Cup dataset. In the DAHCC dataset, multiple activities can occur at the same time event (e.g. eating a meal while watching TV). Analyses were performed combining these activities together (e.g. eatingMealWhileWatchingTv).. However, this resulted in too sparse labels and training a model on these sparse labels created a non generalizable solution. Therefore, only the most dominant activity, which was the activity which occurs the most in the overall dataset, was kept (here eating meals). As some activities were only performed by a single participant or by a small group of participants, only activities occurring more than one hour in total, over all participants, in the dataset (which means for labels provided every 30 seconds, that a specific label should occur more than 120 times in the dataset to be considered). This was done to ensure enough labelled events could be provided during the training phase for each activity group. The activities who did not meet these criteria were labelled in one, general class: "Other". In total, an evaluation on 11 activities was performed: DrinkPreparation, Eating, Organizing, PreparingMeal, Showering, Toileting, UsingMobilePhone, Walking, WatchingTVActively, Working and Other.

For the UCAmI Cup TALK KG and DAHCC TALK KG, INK embeddings till depth 11 were generated. As the events in both KGs are obtained for every 30 seconds, the events of interest in both datasets take into account all the past events in the last 5 minutes. This means that the ML model trained upon these INK embeddings will have to decide which activity is performed based on the last 5 minutes of available data. To analyse the influence of taking into account previous events, a comparison was made using INK embeddings till depth 3 (so, without taking into account previous events) from the UCAmI Cup TALK KG

A clear training and test set was provided for the UCAmI Cup dataset. The train set contained 7 days of continuous sensor data of one person and according labelled activities. The test set contained 3 days of sensor data from the same person, obtained directly after the 7 days in the training set. the TALK approach is evaluated according to this provided split. The generated INK embeddings were provided to an Extra-tree classifier with 1000 estimators. This classifier was chosen based on previous experiments of INK on defined benchmark datasets [31]. Class weights were calculated based on the labels in the training set using the following formula to cover the imbalance in the dataset:

$$\frac{\text{number of samples in training set}}{\text{number of classes} * \text{Count of number of occurrences of each label}}.$$

The DAHCC dataset did not contain such a predefined split and also had a lot more samples and activities to predict. A participant leave-one-out cross validation evaluation was performed to show the benefits of TALK to predict activities for an unseen DAHCC participant. The generated INK embeddings were provided to an Multiclass Catboost model as more categorical data was provided in this dataset. To avoid overfitting, the Catboost number of iterations are evaluated against a validation set. This validation set is created using a group shuffle split on the original train samples. Again class weights were provided to cover the imbalance in the dataset following the same formula described above.

All evaluations were performed on an Intel(R) Xeon(R) CPU E5-2650 v2 @ 2.60GHz processor with 32 cores and 128gb RAM. For both evaluations, results are provided in the form of the accuracy metric, the weighted F1 score and confusion matrices. All experiment code was made available on our repository[5].

5.1. UCAmI Cup results

As originally indicated by UCAmI Cup competition, the accuracy and F1 results were measured on the hold-out test set are provided in Table 5. A test was performed for both INK embeddings at depth 3 and depth 11.

Table 5: TALK accuracy and weighted F1 score results for the UCAmI cup test set

Method	Accuracy	Weighted F1 score
TALK depth 3 with Extra-tree classifier	61.54%	0.6749
TALK depth 11 with Extra-tree classifier	76.44%	0.7744

The normalised confusion matrix for each predicted activity in the test set using the INK embeddings at depth 11 is shown in Figure 4

Our classifier has difficulties to predict when a visitor is at the door of the lab. This activity is confused with entering the lab as both actions are

[5] https://github.com/predict-idlab/TALK

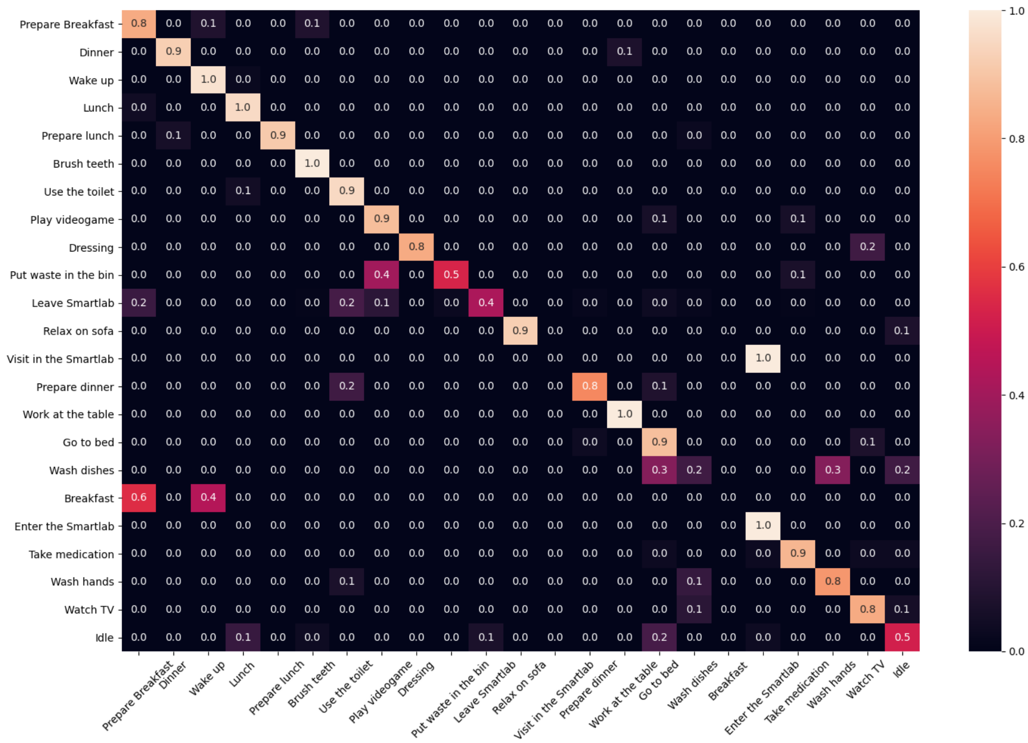

Figure 4: Normalised confusion matrix for all test set predictions of the UCAmI dataset, using the TALK approach.

closely related to each other. The model also has difficulties distinguishing breakfast from preparing breakfast and waking up. Other activities which were difficult to classify are putting waste in the bin and washing dishes.

5.2. DAHCC results

All leave-one-user-out obtained prediction results are averaged together for the DAHCC dataset and are visualised in Table 6. This summary table shows the precision, recall and F1-score for each predicted class that occurred more than 120 times in the dataset as described above. The total level indicates how many of these labels could be found in the dataset. The total accuracy score is calculated based on the following formula:

$$\text{accuracy} = \frac{\sum_C \frac{\text{True Positive C+True Negative C}}{TotalC}}{\text{Amount of classes}}$$

With C one of the 11 classes and the true positives and true negatives for each class can be calculated based on the precision ($\frac{\text{True Positives}}{\text{True Positives+False Positives}}$), the recall ($\frac{\text{True Positives}}{\text{True Positives+False Negatives}}$) and the fact that Total amount of samples per class = True Positives + True Negatives + False Positives + False Negatives. The Macro average score of the precision, recall and F1-score can be calculated by the sum of all individual class results divided by the amount of classes. The weighted average is calculated similarly, but it multiplies the individual scores by the portion of actual occurrences of the class in the dataset before summing all these results and dividing it by the total number of classes.

Table 6: Summary overview of the leave-one-user-out DAHCC evaluation. Precision, recall, F1-score and total values are provided for both individual classes, as accuracy and the macro and weighted averages for the whole evaluation set.

	precision	recall	F1-score	Total
DrinkPreparation	0.15	0.45	0.23	363
Eating	0.37	0.44	0.40	2428
Organizing	0.39	0.39	0.39	1247
Other	0.61	0.43	0.50	2892
PreparingMeal	0.83	0.71	0.77	2026
Showering	0.71	0.81	0.76	454
Toileting	0.64	0.78	0.70	685
UsingMobilePhone	0.30	0.40	0.34	753
Walking	0.58	0.85	0.69	1039
WatchingTVActively	0.56	0.60	0.58	1013
Working	0.86	0.78	0.82	11238
accuracy			0.66	24138
macro avg	0.54	0.60	0.56	24138
weighted avg	0.69	0.66	0.67	24138

The normalised confusion matrix for each predicted activity in the test set is shown in Figure 5

6. Discussion

In this section, both the predictive performance of the TALK methodology and its interpretability are discussed.

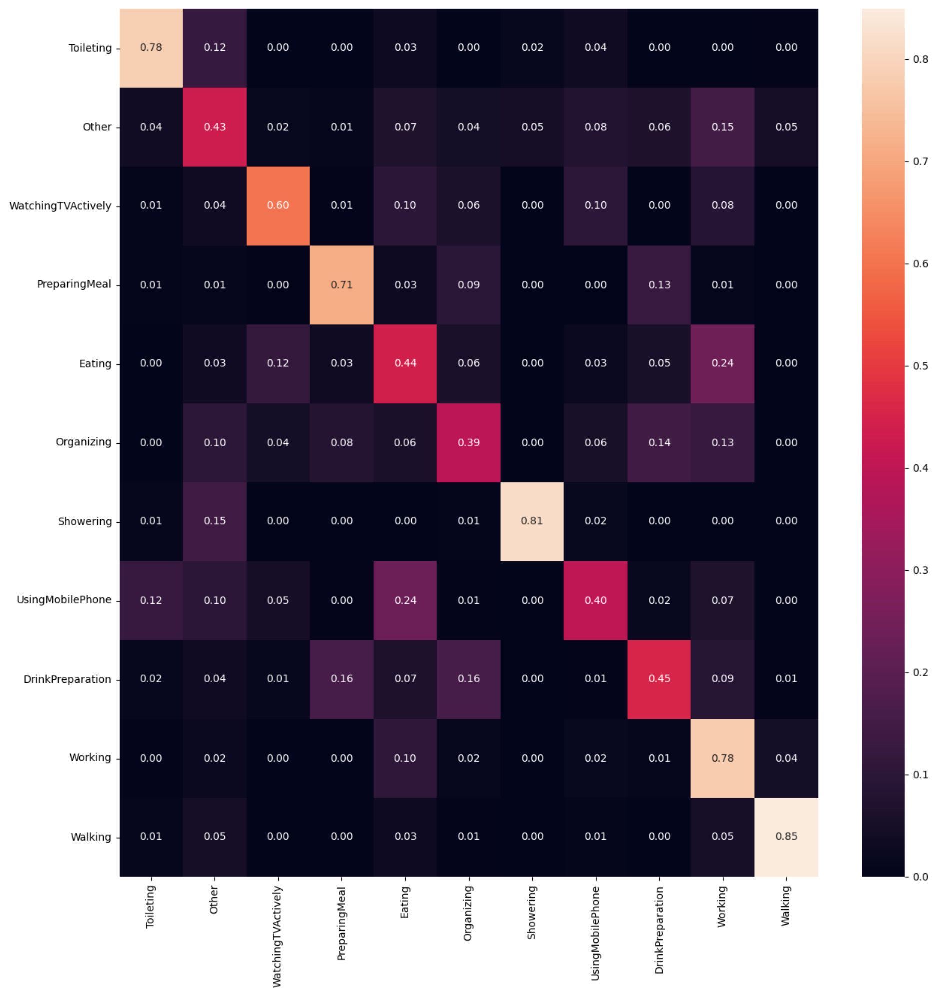

Figure 5: Normalised confusion matrix for all leave-one-participant-out evaluation of the DAHCC dataset, using the TALK approach.

6.1. TALK compared to other approaches

By evaluating TALK on the UCAmI Cup dataset, we are able to compare the obtained results of Table 5 to other solutions generated in the past. Table 7 shows the predictive performance of TALK against previous UCAmI Cup competitors. These results show that our TALK approach outperformed all traditional ML models (e.g., Random Forests, Neural Networks and Naive Bayes classifiers). It also performed better than the Multi-input Temporal ensemble, which is a Deep Learning (DL) technique that fuses several sensor inputs together and makes predictions for a large number of windows (here 30s, 15s, 10s, 6s and 5s windows). Predictions for each of these windows are later on combined to decide which activity happened in the last 30s. The different results in Table 5 also show the influence of using the information of previous events in this evaluation. The results using INK embeddings at depth 11 are significantly higher than when using the INK embeddings without incorporating past events (at depth 3).

Our model does perform worse than the Finite Automata model. However, this approach is especially designed to work with the given competition data. The Finite Automata approach is tailored to the tasks and context (e.g. the smart lab), making them not directly adaptable towards other use cases. The evaluation of new data by this approach has to be performed offline, which makes it hard to make these automata operational in a real-time setting. Finite Automata also takes into account the previously performed activity and uses probabilistic reasoning to determine which activity comes next. Our TALK approach does not take into account these previously performed activities.

Other data-driven research exists that achieves more comparable results as our TALK approach, but in these approaches the original UCAmI Cup activity labels were modified (some labels were aggregated together to boost the performance and making it a more easy classification problem) [33]. During our evaluations of the used models in Table 7 the original UCAmI Cup dataset was used as is, without any modification to compare with the created competition models.

Table 7: Summary of the results obtained by other UCAmI cup participants.

Method	**Accuracy**
Markov Model + NN [34]	45%
Random Forest [35]	47%
Neural Network [36]	60.10%
Naive Bayes Classifier [15]	60.50%
Multi-input Temporal Ensemble [37]	73%
TALK (with INK depth 11 embeddings)	**76.44%**
Finite Automata [20]	90.65%

TALK can be used in different scenarios as shown in the DAHCC evaluation. Both DAHCC and UCAmI Cup evaluations are, however, hard to compare to each other. The UCAmI Cup tries to make predictions for the next couple of days, for a single user, while the DAHCC evaluates one day of lifestyle activities for a new, unseen participant.

In Table 6 and within the confusion matrix of Figure 5, most DAHCC activities were also predicted correctly by our TALK approach. However, some activities have a rather low prediction outcome. As the DAHCC dataset is captured in a free living environment, giving an accurate representation of real life activities, it can happen that different activities are performed in similar conditions. This is clearly the case for the activities: "Working" and "Eating", which were, in the context of the DAHCC dataset, occurred in the same place and as almost all participants just took their lunch while working. Also more general activities like "Organizing" can be performed at any time in every room, and therefore conflicts with many other performed activities. In the context of our use case regarding enriching the personal call systems of elderly, the most important activities like going to the toilet, preparing meals, showering and going out for a walk can be detected by the TALK approach and will deliver useful information to the operator which has to decide the appropriate action.

As stated in the description of the evaluation setup (Section 5), one general class "Other" was created to combine all labels that do not occur more than 120 times in the DAHCC dataset. This set of "Other" activities is quite diverse, and in combination with the ML classifier. which takes into account the class weights, the results of this class are rather low. More of these event samples will probably improve the "Other"'s class predictability. One could evaluate this whole setup without taking into account any of these activities that occur less than 120 times (removing them instead of relabelling them to one class). This would, however, reduce the applicability of such a model in a real-life, streaming context where these lower activities do occur and will then be mapped on one of the provided classes. By creating the "Other" class, we do already have the possibility to see the model's performance in those cases.

6.2. TALK's Interpretability

The TALK approach uses the INK embedding to represent the obtained KG into a tabular format. A wide range of KG embedding techniques however exist. In the evaluations of Section 5, INK already showed that it can handle both categorical data (in the format of binary vectors) as well numerical values. These numerical values frequently occur in the context of sensor observations, which justifies the usage of INK in this context.

INK also keeps a level of interpretability, similar to the interpretability levels of the original KG. The created INK column features still have a human interpretable aspect and can be analysed to see which features, or nodes and edges within our original KG had an effect during the classification of events. To show this benefit, besides the INK representation, the INK implementation also contains semantic rule mining modules[6] and is able to mine task-specific rules given a set of positive and negative samples [38]. An experiment was performed where for each of the 12 selected classes in the DAHCC dataset, a task-specific semantic rule miner was trained using INK. As a positive set, we used all positive samples for one class, while all other samples not from this class were used as negative evidence. A summary of the some found rules in combination with their predictive performance is provided in Table 8. They Show that several values regarding the phone, humidity level in the kitchen and the current off state of the television have a high impact on the fact that someone is working or not. Also the fact that water is being taken from the kitchen faucet and the loudness value increases in the kitchen indicates whether or not someone is eating a meal. The last two rules indicate whether a person is watching TV or going to the toilet. For the last rule, one can see that the fact that the toilet light changes in a previous event regarding the current event is a crucial aspect in the detection of this particular activity.

The whole approach shows that the used TALK approach in combination with INK can create an interpretable tool to track activities in a smart home environment.

7. Conclusion

In this work, TALK, a new hybrid AI approach to track human activities using linked knowledge is proposed and evaluated in detail. The results showed that both a high predictive performance and the ability to adapt to different use cases within this domain can be delivered by this new methodology. The TALK approach is competitive with knowledge-driven approaches by providing interpretable outcomes in the form of simple interpretable rules. While still can incorporate new information and learn from those cases such as the data-driven variants.

[6]https://github.com/IBCNServices/INK/tree/master/ink/miner

Table 8: INK task-specific rule mining precision and recall results on the DAHCC dataset.

Rule	**Prec.**	**Rec.**
Prev.Prev.phone.MagnetometerX.MinValue < -541.9 and Prev.Prev.Kitchen.humidity.MaxValue <= 62.5 and Living.Tv§off and Prev.Prev.Wearable.AccelerationZ.MeanValue > 31.62 =>Working	0.89	0.74
Prev.Prev.phone.GravityY.MaxValue <= 0.0017 and Prev.phone.LocationLatitude.MaxValue > 51.012 and Prev.Kitchen.Peopledetected.MeanValue <= 0.84 and Kitchen.EnvironmentWaterrunning and floorKitchen.Loudness.MaxValue > 44.5 =>EatingMeal	0.67	0.27
Prev.Localisation.location§living and Prev.phone.AccelerationY.MeanValue > -6.59 and Kitchen.Window§closed and Living.Tv§on =>WatchingTVActively	0.86	0.68
Prev.Living.PeoplePresence.MinValue <= 0.5 and Prev.Toilet.Light.MinValue <= 988.5 and Toilet.Light.MeanValue > 494.25 =>Toileting	1.0	0.65

As future work directions we see additional resources and even made predictions to be linked back to the TALK KG to provide even more information to embed. The TALK approach could take the previous predictions into account by adding an additional relationship to each event. The INK embedding would then also generate a new feature column based on this information. Similarly, predictions from other ML models could also be incorporated in the TALK KG. Another research direction can also extend the TALK approach towards other domains, which also uses a combination of domain knowledge and sensor data to predict event-related outcomes.

Reproducibility

The created TALK KGs, the used INK embeddings, the files to create those KGs and embeddings, and the full evaluation pipelines are all made available on our Github repository[7]. INK is also made available on another Github repository[8]. The DAHCC ontology and dataset is also made available open-source[9]

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