

Article

Fine-Grained Mapping Between Daily Activity Features in Smart Homes

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Abstract: For daily activity recognition in smart homes, it is possible to reduce the effort required for labeling by transferring a trained model. This involves utilizing a labeled daily activity dataset from one smart home to recognize other activities in another. The foundation of this transfer lies in establishing a shared common feature space between the two smart homes, achieved through a feature mapping approach for daily activities. However, existing heuristic feature mapping methods are often coarse, resulting in only moderate recognition performance. In this paper, we propose a fine-grained daily activity feature mapping approach. Sensors are ranked by their significance using the PageRank algorithm, and a novel alignment algorithm is introduced for sensor mapping. Experiments conducted on the publicly available CASAS dataset demonstrate that the proposed method significantly outperforms existing daily activity feature mapping approaches.

Keywords: PageRank; smart home; daily activity features mapping

1. Introduction

One of the goals of smart homes is to support residents in living independently by recognizing their daily activities [1]. Smart homes achieve this through the use of non-invasive sensors that monitor residents' activities and status [2,3]. As residents perform daily activities, these sensors are continuously activated, generating a stream of sensor events. Daily Activity Recognition (DAR) focuses on identifying the category of daily activity based on the generated sensor event streams [4].

Developing an effective recognition model is the central focus of Daily Activity Recognition (DAR). Numerous approaches have been proposed to generate such models [5–12]. Among these, data-driven methods treat DAR as a multi-class classification problem, with supervised machine learning techniques being widely applied. While these supervised approaches often achieve high recognition performance, they require a substantial amount of labeled data, which can be labor-intensive to obtain. To reduce the effort of data labeling and make the most of existing recognition models, transferring a trained model from one smart home to another has emerged as a promising area of study [13].

When transferring a trained recognition model, it is essential to identify shared features of daily activities performed by residents in two smart homes. Sensors are the primary source of such features, making effective sensor mapping between the two environments a fundamental step in generating shared activity features. While the sensor layouts may differ between smart homes, the categories of sensors and functional areas tend to remain relatively consistent. As a result, most existing approaches map sensors on the basis of their categories or the functional areas they are associated with. In these methods,



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sensors with the same category or those located in similar functional areas are mapped together. Although such coarse mapping methods are straightforward and practical, they often result in only moderate performance for Daily Activity Recognition (DAR) [14]. To enhance DAR performance, this paper proposes a fine-grained sensor mapping approach. In addition to considering sensor categories and functional areas, this method incorporates the significance degree of sensors for mapping. The entire mapping process is automated and does not require manual intervention or labeling information from daily activity instances in the target smart home.

The major contributions of this paper are summarized as follows:

1. A novel algorithm for calculating the significance degree of sensors is proposed.
2. A strategy for sensor alignment is presented to improve the mapping process.
3. The proposed approach is evaluated using a public dataset, demonstrating its effectiveness.

The remainder of this paper is organized as follows: Section 2 reviews related works. Section 3 details the proposed approach. Section 4 presents the experimental evaluation and results. Section 5 concludes the study and discusses potential future directions.

2. Related Work

The establishment and transfer of DAR models are two primary focal areas in the field of Daily Activity Recognition (DAR).

2.1. DAR Model Establishment

For DAR model establishment, only a single smart home is involved, and the same data distribution is utilized. Three key issues are typically addressed during the establishment of a DAR model.

The primary challenge in DAR model establishment is how to effectively segment the sensor event stream. Over a given period, numerous daily activity instances are performed, resulting in a continuous stream of sensor events. To recognize the category of each activity instance, the activated sensor event stream must be segmented accurately. Early approaches focused on segmentation algorithms using fixed windows, defined by either a fixed number of sensor events or a fixed duration [15,16]. While these methods are straightforward to implement, they often yield poor recognition performance. This is because the number of activated sensor events and their durations vary significantly between activity instances. Consequently, sensor events from multiple activities may be grouped into the same window, or events from a single activity may be split across multiple windows. To address these limitations, segmentation algorithms based on whole daily activity instances have been developed. Wan et al. observed that sensor events activated by the same activity are spatially and temporally close. They proposed a relevancy degree formula to measure the relationship between adjacent sensor events, segmenting the stream when the relevancy degree exceeds a specified threshold [17]. Similarly, Aminikhanghahi et al. extracted additional features from sensor events and introduced a change-point detection algorithm for time-series data [18]. Although segmentation algorithms based on entire activity instances improve recognition performance, they often require specialized algorithms and are challenging to apply in real-time DAR scenarios [19].

The second challenge in DAR model establishment is how to extract meaningful features from the sensor event stream to represent daily activities. There are two primary approaches for feature extraction. The first approach involves manually defining the feature space. For example, the equipped sensors themselves are often used as the feature space. Additionally, frequently mined items or sequences from the sensor event stream can serve as the feature space [20,21]. Once the feature space is defined, methods such as activated frequency, density [22], TF-IDF [23], and mutual information [24] are commonly employed

to calculate feature values. The second approach generates the feature space automatically. For instance, Gochoo et al. used 2D Convolutional Neural Networks (CNNs) to extract features by representing the sensor event stream as images, with sensor events mapped to pixels or grayscale values. This approach is inspired by applications where CNNs are used to extract features from images [25]. Additionally, recognizing the similarity between sensor event streams and natural language sequences, Ghods et al. and Bouchabou et al. proposed feature extraction models based on Seq2Seq and Word Embedding techniques, respectively [26,27]. Compared to the first approach, the second approach allows for the extraction of more complete and discriminative features, potentially improving the accuracy of daily activity recognition.

The final challenge in DAR model establishment is how to develop an effective model for recognizing daily activities. Approaches to developing DAR models can be categorized into two main types: data-driven approaches and knowledge-driven approaches. Data-driven approaches typically treat DAR as a classification task [28–33]. As such, a variety of classification models are used, such as Naïve Bayes (NB) [28], Hidden Markov Models (HMM) [34], Support Vector Machines (SVM) [35], Conditional Random Fields (CRF) [36], Random Forests (RF) [37], Ensemble Learning [38,39], Formal Concept Analysis (FCA) [40], and Long Short-Term Memory (LSTM) networks [41], along with their variants. Knowledge-driven approaches, on the other hand, leverage prior knowledge about the world to build activity models using knowledge representation techniques. Many of these approaches rely on basic ontologies or their variants. For example, Chen et al., Rodriguez et al., Noor et al., Gayathri et al., and Civitarese et al. developed various types of ontologies, such as basic ontology [42], fuzzy ontology [43], imprecise ontology [44], and probabilistic ontology [45,46], to support DAR. While knowledge-driven approaches are effective in using structured domain knowledge, they struggle with handling noise and uncertainty in sensor data. In contrast, data-driven approaches, which are trained on realistic data, are better equipped to manage the randomness and variability inherent in daily activities. However, a limitation of data-driven approaches is that the models they produce are often environment-specific and tailored to the trained subject, making them less adaptable to different settings [47,48].

2.2. DAR Model Transfer

To alleviate the burden of labeling, DAR model transfer has gradually gained attention. The goal of DAR model transfer is to adapt an established model for use in recognizing daily activities in another smart home. Two key focuses in DAR model transfer are unifying the feature space of daily activities and minimizing the differences between data distributions across different smart homes.

As mentioned earlier, equipped sensors are primary features for daily activity recognition, and sensors are typically categorized by their type and the functional areas they serve [49]. Sensor mapping is a crucial method for unifying the feature space of daily activities [50]. To the best of our knowledge, existing sensor mapping approaches typically group sensors by category and/or function area. Sensors from different smart homes that share the same group label are then mapped together. In some cases, the sensor mapping process can be further refined manually [51].

For the second focus of DAR model transfer, transfer learning has been widely adopted by most existing approaches. Chiang et al. introduced a feature-based knowledge transfer framework [14], which utilized transfer learning to relax the requirement that training and testing datasets must have highly similar distributions. Their evaluation showed that the framework outperformed non-transfer learning models by 8% in terms of accuracy. Wemlinger et al. developed a shared semantic feature space, where the parameters of

the space were optimized according to the differences between data distributions. Model-based transfer learning has also been used for DAR [52]. For example, Hu et al. employed divergence, based on the probability distributions of sensors, to evaluate the similarity between instances of daily activities. The most similar activity instances were assigned the same labels [53]. Myagmar et al. proposed a novel heterogeneous transfer learning algorithm called Heterogeneous Daily Living Activity Learning (HDLAL) [54]. HDLAL projected data from two domains into a common feature space using the maximum mean discrepancy. From this, a domain-invariant feature representation was derived from the cross-domain data distribution. An ensemble classification algorithm was then used to train a multi-label classifier in the new feature space. Finally, the projected data was used to predict the labels of daily activity instances. In addition to transfer learning, ontology-based approaches have also been explored. Ye et al. developed ontologies for daily activity recognition in two smart homes. The differences between activity instances were addressed by extracting parameters from the respective ontologies. An integrated classifier was then employed for DAR based on these differences [51].

3. The Proposed Approach

The proposed approach is outlined as follows. First, the category and functional area of each sensor installed in the two smart homes are identified. Additionally, two streams of sensor events collected from the smart homes over a specific period are provided. Second, the significance level of each sensor is determined based on the dependencies extracted from the sensor event streams. Third, the sensors in each smart home are grouped according to their category and functional area. Finally, sensors within the same group are clustered based on their significance levels, and an alignment algorithm is applied to map clusters between the two smart homes.

3.1. Preliminary

To better describe the proposed method, we first provide some formal terms related to the method.

Definition 1. For a given smart home SH , $FA(SH) = \{fa_1, fa_2, \dots\}$ represents the **set of functional areas** within SH .

Definition 2. For a given smart home SH , $SC(SH) = \{sc_1, sc_2, \dots\}$ represents the **set of categories of equipped sensors** within SH .

Definition 3. For a given smart home SH , $SEN(SH) = \{s_1, s_2, \dots\}$ represents the **set of equipped sensors** within SH .

Definition 4. For a given smart home SH and $s \in SEN(SH)$, $s = (id, ca, fa)$ is defined as a **sensor**, where $s.id$ represents the sensor's unique identifier, $s.ca$ denotes its category, and $s.fa$ indicates the functional area where it is installed. For example, $s = (M008, M, bedroom)$ specifies a sensor with the identifier "M008" and the category "M", installed in the bedroom.

Definition 5. For a given smart home SH , $DAC(SH) = \{da_1, da_2, \dots\}$ represents the **set of categories of involved daily activities** within SH .

Definition 6. For a given smart home SH and $s \in SEN(SH)$, a **sensor event** $ev(s) = (d, t, s.id, v, dal)$ is defined, where d and t represent the date and time of the event, v denotes the sensor's recorded value, and dal indicates the category of the daily activity triggered by the activation of s .

Definition 7. For a given smart home SH and $s_1, s_2 \in SEN(SH)$, $ev(s_1)$ is defined as the **precursor** of $ev(s_2)$, and $ev(s_2)$ is defined as the **successor** of $ev(s_1)$ if either $ev(s_1).d == ev(s_2).d \wedge ev(s_1).t < ev(s_2).t$ is satisfied or $ev(s_1).d < ev(s_2).d$ is satisfied.

Definition 8. For two sensor events $ev(s_1)$ and $ev(s_2)$, where $ev(s_1)$ is the precursor of $ev(s_2)$. $ev(s_1)$ is called the **direct precursor** of $ev(s_2)$, and $ev(s_2)$ is called the **direct successor** of $ev(s_1)$ if no other event $ev(s)$ such as $ev(s_1) < ev(s)$ and $ev(s) < ev(s_2)$ hold. The notation $ev(s_1) \rightarrow ev(s_2)$ is used to indicate that $ev(s_1)$ is the direct precursor of $ev(s_2)$.

Definition 9. Given n sensor events $ev(s_1), ev(s_2), \dots, ev(s_n)$, the sequence $\langle ev(s_1), ev(s_2), \dots, ev(s_n) \rangle$ is called a **sensor events stream** if $\forall 1 \leq i \leq n - 1, ev(s_i) \rightarrow ev(s_{i+1})$ holds.

For a smart home SH , let $FA(SH) = \{\text{Bedroom, Toilet, Kitchen, Living Room, Shower Room}\}$. Let $SEN(SH) = \{M008, M009, LS008, LS004, LS003, LS016, MA008\}$, where $SC(SH) = \{M, LS, MA\}$ represents the categories, with $\{M008, M009\}$ as infrared motion sensors (M), $\{LS008, LS004, LS003, LS016\}$ as light sensors (LS), and $\{MA008\}$ as wide-area infrared motion sensors (MA). Let $DAC(SH) = \{\text{Sleep, Bath, Cook_Breakfast}\}$ represent daily activities. Table 1 presents a fragment of a sensor event stream activated by the “Sleep” activity, where each line denotes a sensor event. Two adjacent sensor events are direct predecessors or direct successors of each other.

Table 1. A fragment of sensor events stream.

<i>d</i>	<i>t</i>	<i>s.id</i>	<i>v</i>	<i>dal</i>
25 August 2012	15/01	M008	OFF	Sleep
25 August 2012	15/01	M009	ON	
25 August 2012	15/01	M008	OFF	
25 August 2012	15/02	M009	OFF	
25 August 2012	15/03	LS008	25	
25 August 2012	15/05	LS004	31	
25 August 2012	15/06	LS003	3	
25 August 2012	15/07	LS016	8	
25 August 2012	15/07	LS004	8	
25 August 2012	15/09	LS008	24	
25 August 2012	15/09	MA008	OFF	

3.2. Significance Degree

The adjacency relationships between sensor events in a given sensor event stream can be naturally represented as a directed graph. For instance, the directed graph corresponding to the sensor event stream shown in Table 1 is depicted in Figure 1, where sensors are nodes and the adjacency relationships between sensor events are represented by edges. Inspired by the PageRank algorithm, which is designed to evaluate the significance of web pages [55], we propose that the significance degrees of sensors can be determined using the PageRank algorithm, treating sensors as web pages and the adjacency relationships between sensor events as link relationships between web pages.

PageRank is used to rank web pages based on their importance. It assumes that a web page linked by many others will have a higher ranking, and a page linked by high-ranking pages will also receive a relatively high ranking. Inspired by this concept, this article proposes a new algorithm to rank entity pairs according to their credibility. The algorithm

is described as follows: Let P be the set of all involved web pages, and $u \rightarrow v$ denotes that web page v is linked to web page u . Let R be the set of pairs $\{(u, v) \mid u \rightarrow v, u, v \in P\}$. Assign $F(u)$ and $B(u)$ to $\{v \mid (u, v) \in R\}$, representing the set of web pages that link to u and the set of web pages that v links to, respectively.

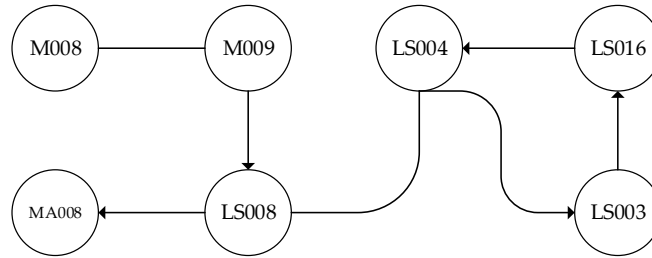


Figure 1. Directed graph corresponding to the sensor events stream shown in Table 1.

Based on this approach, Algorithm 1 is proposed to compute the significance degree of sensors. First, the activation frequency and percentage of each sensor are calculated from the given sensor event stream EV , as shown in lines 2–8 of Algorithm 1. Additionally, the PageRank algorithm is used to determine the significance degrees of each sensor, as outlined in lines 9–21. In this context, $pg(s)$ represents the PageRank value of a sensor.

Algorithm 1.

Input: smart home SH
 sensor events stream $EV = \langle ev(s_1), ev(s_2), \dots, ev(s_n) \rangle$, where $\forall 1 \leq i \leq n - 1, ev(s_i) \in SEN(SH)$
 decay factor d
Output: set of significance degrees of sensors
 $PG(SH) = \{(s_1, pg(s_1)), (s_2, pg(s_2)), \dots\}$

1. $sum \leftarrow 0$
2. **for each** s **in** $SEN(SH)$
3. solve the frequency $f(s)$ of s which is activated in EV .
4. $sum \leftarrow sum + f(s)$
5. **end for**
6. **for each** s **in** $SEN(SH)$
7. $pg(s) \leftarrow f(s) / sum$
8. **end for**
9. **while**(true)
10. **for each** s **in** $SEN(SH)$
11. $IN(s) \leftarrow \{s^* \mid ev(s^*), ev(s) \in EV \wedge ev(s^*) \rightarrow ev(s)\}$
12. **for each** s^* **in** $IN(s)$
13. $OUT(s^*) \leftarrow \{s^\# \mid ev(s^*), ev(s^\#) \in EV \wedge ev(s^*) \rightarrow ev(s^\#)\}$
14. $pg(s) \leftarrow d * pg(s^*) / |OUT(s^*)|$
15. **end for**
16. $pg(s) \leftarrow 1 - d + pg(s)$
17. **end for**
18. **if** the rank of each $s \in SEN(SH)$ stops changing by $pg(s)$ **then**
19. **break**
20. **end if**
21. **end while**
22. **return** $PG(SH)$

3.3. Coarse Sensors Mapping

Sensors can be classified by category and function area. For a given smart home SH , the set of equipped sensors $SEN(SH) = \{s_1, s_2, \dots\}$ can be partitioned into subsets $P_SEN(SH) = \{P_1, P_2, \dots\}$. Each subset $P \subseteq SEN(SH)$ satisfies the conditions: $(\forall s_1, s_2 \in P, s_1.ca == s_2.ca) \wedge (\forall s_1, s_2 \in P, s_1.fa == s_2.fa)$. Additionally, for any two distinct subsets $P_1 \subseteq SEN(SH)$ and $P_2 \subseteq SEN(SH)$, the conditions $P_1 \neq P_2$ imply: $(P_1 \cap P_2 == \emptyset) \wedge (\forall s_1 \in P_1, s_2 \in P_2, s_1.fa \neq s_2.fa \vee s_1.ca \neq s_2.ca)$.

Given two smart homes $SH1$ and $SH2$, P^* and $P^\#$ represent the set of equipped sensors within $SH1$ and $SH2$, respectively. Coarse sensors mapping $CM = \{(P^*, P^\#) \mid P^* \in P_SEN(SH1) \wedge P^\# \in P_SEN(SH2) \wedge \forall s^* \in P^*, s^\# \in P^\#, s^*.ca == s^\#.ca \wedge s^*.fa == s^\#.fa\}$ can be established between $P_SEN(SH1)$ and $P_SEN(SH2)$. For instance, consider sensors s_1 and s_2 equipped in two different smart homes. Both s_1 and s_2 are infrared motion sensors and are installed in the bedroom. Therefore, s_1 is mapped to s_2 in the fine sensor mapping.

Algorithm 2 is used for fine sensor mapping based on coarse sensor mapping. First, the significance degree of each sensor is calculated, as shown in lines 3–4. Then, the significance degrees are clustered, and the clusters are ranked by the value of their centroids, as shown in line 5. Note that for $\forall 1 \leq i \leq |\{PG^{*1}, PG^{*2}, \dots\}|$, the centroid of PG^{*i} is greater than centroid of PG^{*i+1} . Next, the maximal subset of successive alternate clusters is identified, where the sensors of two adjacent clusters come from different smart homes, as shown in lines 7–18. Then, fine pg value mappings are determined by iteratively searching for the most similar clusters from the maximal subset of successive alternate clusters, as shown in lines 19–27. Finally, the function `getSensorsMapping` is used to generate the fine sensor mappings corresponding to the fine pg value mappings. Figure 2 illustrates Algorithm 2. PG^* and $PG^\#$ represent two sets of sensor significance degrees generated from two different smart homes, respectively. For example, in PG^* , the pair $(s^*_1, 0.35)$ indicates that the significance degree of sensor s^*_1 is 0.35. Using these significance degrees, sensors are clustered within both PG^* and $PG^\#$. For instance, $(s^*_2, 0.26)$ and $(s^*_5, 0.22)$ belong to the same cluster. After clustering, all clusters in PG^* and $PG^\#$ are ranked by their centroid values. Clusters are then segmented if two consecutive clusters are from either PG^* or $PG^\#$, resulting in the creation of A_PG . For example, the sequence $\{0.35\}, \{0.28, 0.25, 0.21\}, \{0.26, 0.22\}, \{0.14, 0.12\}$, and $\{0.09, 0.07\}$ forms an element of A_PG . Finally, adjacent clusters with the smallest centroid difference in A_PG are grouped together, and the corresponding sensors are mapped.

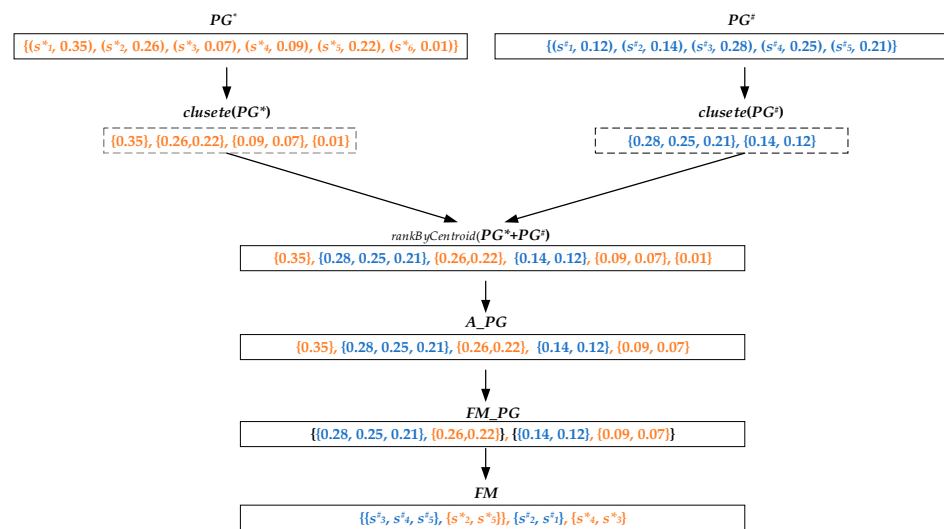


Figure 2. Illustration for Algorithm 2.

Algorithm 2.**Input:** two smart homes SH_1, SH_2 set of coarse sensors mapping CM between SH_1, SH_2 significance degrees $PG(SH_1)$ and $PG(SH_2)$ **Output:** set of fine sensors mapping FM

```

1.    $FM\_PG \leftarrow \emptyset$ 
2.   for each  $(P^*, P^\#)$  in  $CM$ 
3.      $PG^* \leftarrow \{(s, pg(s)) \mid s \in P^*\}$ 
4.      $PG^\# \leftarrow \{(s, pg(s)) \mid s \in P^\#\}$ 
5.      $\{PG^{*1}, PG^{*2}, \dots\} \leftarrow \text{rankByCentroid}(\text{cluster}(PG^*)^* + \text{cluster}(PG^\#))$ 
6.      $A\_PG \leftarrow \emptyset$  // maximal subset of successive alternate clusters
7.      $p \leftarrow 1$ 
8.     while  $(i \leq |\{PG^{*1}, PG^{*2}, \dots\}| - 1)$ 
9.       if  $(PG^{*i}, PG^{*i+1} \in \{PG^{*1}, PG^{*2}, \dots\}$  or  $PG^{*i}, PG^{*i+1} \in \{PG^\#_1, PG^\#_2, \dots\})$  then
10.        if  $flag == \text{false}$  then
11.           $A\_PG \leftarrow A\_PG \cup \{PG^{*p}, \dots, PG^{*i}\}$ 
12.           $flag \leftarrow \text{true}$ 
13.        end if
14.         $p \leftarrow i + 1$ 
15.      else
16.         $flag \leftarrow \text{false}$ 
17.      end if
18.       $i \leftarrow i + 1$ 
19.    end while
20.    for each  $\{PG^{*a1}, PG^{*a2}, \dots\}$  in  $A\_PG$ 
21.       $T \leftarrow \{PG^{*a1}, PG^{*a2}, \dots\}$ 
22.      while  $(T! = \emptyset \text{ and } |T|! = 1)$ 
23.         $(PG^{*ai}, PG^{*ai+1}) \leftarrow \text{minCentroidDifference}(T)$ 
24.         $FM\_PG \leftarrow FM\_PG \cup \{(PG^{*ai}, PG^{*ai+1})\}$ 
25.         $T \leftarrow T - \{PG^{*ai}, PG^{*ai+1}\}$ 
26.      end while
27.    end for
28.     $FM \leftarrow \text{getSensorsMapping}(FM\_PG)$ 
29.  return  $FM$ 

```

4. Results and Evaluation**4.1. Smart Homes and Collected Datasets**

We conducted experiments using six smart homes—“HH101”, “HH105”, “HH110”, “HH109”, “HH114”, and “HH123”—along with the corresponding datasets published by the Center for Advanced Studies in Adaptive Systems (CASAS) at Washington State University [56]. The smart homes were divided into two groups based on their characteristics: Group A includes “HH101”, “HH105”, and “HH110”, while Group B includes “HH109”, “HH114”, and “HH123”. The sensors installed in the homes within the same group were used to evaluate the proposed approach. Table 2 shows the layouts of the six smart homes, and Table 3 lists the number of sensors in each smart home categorized by sensor type. The installed sensors are categorized into seven types: “temperature sensor (T)”, “infrared motion sensor (M)”, “wide-area infrared motion sensor (MA)”, “light sensor (LS)”, “light switch sensor (L)”, “temperature sensor (T)”, “battery sensor (BATV and BVTP)”, and

“door switch sensor (D)”. For Groups A and B, the common daily activity categories are shown in Table 4.

Table 2. Layouts related to six smart homes.

	Kitchen	Dining	Parlor	Porch	Toilet	Bedroom
HH101, HH105, HH110	1	1	1	1	1	1
HH110, HH114, HH123	1	0	1	1	1	1

Table 3. Number of equipped sensors in six smart homes grouped by category of sensors.

	D	LS	M	MA	BATP	BATV	T	L
HH101	3	16	12	4	18	18	5	0
HH105	5	18	13	5	23	23	5	6
HH110	5	15	11	4	19	19	4	6
HH109	7	17	14	3	20	20	4	2
HH114	3	13	4	9	16	16	3	8
HH123	1	14	5	9	6	17	6	0

Table 4. Shared activity categories.

Smart Homes	Activity Categories
HH101, HH105, HH110	Bathe, Bed_Toilet_Transition, Cook_Breakfast, Cook_Dinner, Dress, Eat_Breakfast, Eat_Dinner, Enter_Home, Evening_Meds, Groom, Leave_Home, Morning_Meds, Personal_Hygiene, Relax, Sleep, Sleep_Out_Of_Bed, Toilet, Wash_Breakfast_Dishes, Wash_Dinner_Dishes
HH109, HH114, HH123	Bathe, Bed_Toilet_Transition, Cook_Breakfast, Cook_Dinner, Cook_Lunch, Dress, Eat_Breakfast, Eat_Dinner, Eat_Lunch, Enter_Home, Entertain_Guests, Evening_Meds, Groom, Leave_Home, Morning_Meds, Personal_Hygiene, Phone, Read, Relax, Sleep, Sleep_Out_Of_Bed, Toilet, Wash_Breakfast_Dishes, Wash_Dinner_Dishes, Wash_Dishes, Wash_Lunch_Dishes, Watch_TV, Work_At_Table

4.2. Experimental Setup

We validate the proposed approach by evaluating the performance of DAR using the open-source tool Weka 3.8 [57]. For each pair of datasets collected from two different smart homes within the same group, one dataset is used as the training set and the other as the test set.

Three sensor mapping approaches are compared in the evaluation: Approach C: Sensors are mapped if they have the same categories [49]. Approach CF: Sensors are mapped if they have the same categories and function areas [52–54]. Proposed Approach (PA): The proposed approach maps sensors based on the sensor event streams activated by daily activities. These sensor event streams serve as the feature space for daily activity recognition (DAR).

For the DAR task, we employ three classifiers: Bayes Network (BN), Naive Bayes (NB), and Random Forest (RF), along with a Self-Organizing Map (SOM) for clustering. The evaluation metrics used are accuracy and precision, as defined in Equations (1) and (2), respectively. The following terms are used in these metrics:

- TP: The number of true positives, i.e., correctly classified instances using the proposed approach.
- FP: The number of false positives, i.e., incorrectly classified instances using the proposed approach.
- TN: The number of true negatives, i.e., correctly classified negative instances using the proposed approach.
- FN: The number of false negatives, i.e., incorrectly classified negative instances using the proposed approach.

$$\text{Accuracy} = \text{TP} + \text{TN} / (\text{TP} + \text{TN} + \text{FP} + \text{FN}) \quad (1)$$

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP}) \quad (2)$$

4.3. Results

In Table 2, the smart homes HH101, HH105, and HH110 are classified into Group A because they have the same layouts. Similarly, HH110, HH114, and HH123 are classified into Group B. The activities involved in each smart home vary, but only the shared activities within each group are used to test the proposed approach. These shared activities are shown in Table 4. Two independent experiments are conducted to evaluate the proposed approach. The sensor mapping is carried out between any two smart homes within Group A (or Group B). The experimental results for DAR are shown in Tables 5 and 6 (for Group A) and Tables 7 and 8 (for Group B). The headers of columns 3–8 can be divided into two parts, separated by the character “–”. The sensor event streams in the first part are used as the training set, while the streams in the second part are used as the test set. For some classifiers, the best results from each experiment are highlighted in bold. The best results for all classifiers are underlined in bold. It can be observed that the Proposed Approach (PA) outperforms both C and CF. In most comparisons, the performance achieved by PA and CF is significantly better than that of C. Specifically:

Table 5. Comparison of precision of group A.

Classifier	Approach	HH101– HH105	HH105– HH101	HH101– HH110	HH110– HH101	HH105– HH110	HH110– HH105
BN	C	76.9%	<u>85.7%</u>	73.5%	62.4%	72.4%	71.6%
	CF	66.4%	67.0%	69.5%	48.6%	71.1%	58.1%
	PA	<u>79.4%</u>	85.5%	73.8%	<u>65.2%</u>	<u>76.8%</u>	<u>72.2%</u>
NB	C	72.0%	76.3%	61.6%	51.3%	62.2%	65.3%
	CF	70.4%	60.3%	67.2%	49.9%	69.1%	46.6%
	PA	75.2%	77.5%	67.0%	58.4%	69.8%	65.4%
RF	C	72.6%	82.8%	51.6%	26.3%	68.1%	63.4%
	CF	72.5%	71.6%	<u>74.7%</u>	53.7%	70.6%	54.4%
	PA	75.5%	81.7%	54.8%	57.8%	60.0%	67.2%

Table 6. Comparison of accuracy of group A.

Classifier	Approach	HH101– HH105	HH105– HH101	HH101– HH110	HH110– HH101	HH105– HH110	HH110– HH105
BN	C	70.5%	77.4%	31.3%	46.1%	69.4%	69.3%
	CF	55.0%	62.1%	25.1%	46.2%	60.9%	57.0%
	PA	73.6%	78.2%	42.8%	50.8%	73.4%	70.8%
NB	C	66.4%	69.7%	31.9%	28.1%	61.3%	57.5%
	CF	53.5%	52.3%	20.0%	32.4%	49.1%	46.5%
	PA	72.9%	73.0%	33.6%	34.3%	68.7%	60.9%
RF	C	65.0%	50.3%	26.0%	45.8%	64.7%	62.0%
	CF	51.0%	62.6%	20.6%	47.3%	62.8%	61.4%
	PA	70.1%	53.6%	31.9%	46.1%	68.9%	61.0%

Table 7. Comparison of precision of group B.

Classifier	Approach	HH109– HH114	HH114– HH109	HH109– HH123	HH123– HH109	HH114– HH123	HH123– HH114
BN	C	75.0%	71.3%	83.4%	74.6%	83.4%	78.7%
	CF	31.1%	47.5%	46.1%	43.2%	61.6%	57.3%
	PA	77.8%	74.8%	87.0%	79.7%	87.2%	81.4%
NB	C	81.7%	73.1%	81.8%	68.8%	82.5%	81.9%
	CF	41.3%	33.9%	50.3%	34.0%	71.0%	60.0%
	PA	85.1%	73.7%	82.6%	68.4%	84.7%	86.4%
RF	C	78.5%	74.1%	79.6%	75.0%	77.1%	81.9%
	CF	32.0%	32.2%	45.5%	32.5%	63.9%	65.9%
	PA	79.6%	77.0%	82.0%	79.5%	79.0%	84.6%

Table 8. Comparison of accuracy of group B.

Classifier	Approach	HH109– HH114	HH114– HH109	HH109– HH123	HH123– HH109	HH114– HH123	HH123– HH114
BN	C	70.2%	68.5%	79.8%	70.8%	83.3%	77.2%
	CF	32.8%	39.3%	44.8%	46.9%	61.2%	52.9%
	PA	75.0%	72.7%	85.6%	75.2%	87.2%	78.4%
NB	C	74.5%	67.7%	78.2%	63.5%	80.6%	82.0%
	CF	39.0%	32.0%	51.2%	35.4%	69.5%	53.1%
	PA	79.3%	68.1%	81.9%	63.2%	80.3%	85.8%
RF	C	69.2%	67.0%	71.8%	69.5%	79.8%	80.6%
	CF	40.2%	34.2%	48.3%	38.0%	64.4%	62.0%
	PA	70.6%	71.0%	76.0%	75.4%	80.1%	83.6%

For Group A: The average precision achieved by PA increased by 1.73% (using BN) and 4.1% (using NB) compared to CF. When compared to C, the increase was 12.03% (using BN) and 8.3% (using NB). The average precision achieved by PA increased by 5.37% compared to CF (using RF), while it decreased slightly by 0.08% compared to C (using RF).

The average accuracy achieved by PA increased by 4.26% (using BN), 4.75% (using NB), and 2.97% (using RF) compared to CF. Compared to C, the increase was 13.88% (using BN), 14.93% (using NB), and 4.32% (using RF). BN achieved the best average precision and accuracy in most of the comparisons.

For Group B: The average precision achieved by PA increased by 3.59% (using BN), 1.85% (using NB), and 2.58% (using RF) compared to CF. When compared to C, the increase was 33.52% (using BN), 31.73% (using NB), and 34.95% (using RF). The average accuracy achieved by PA increased by 4.05% (using BN), 2.01% (using NB), and 3.14% (using RF) compared to CF. Compared to C, the increase was 32.79% (using BN), 29.73% (using NB), and 28.27% (using RF). Again, BN achieved the best average precision and accuracy in most comparisons.

Each smart home contains n sensors (averaging around 80). Each sensor has approximately m successor sensors (averaging around 3). The process iterates approximately k times (3 times), so the average time complexity is $O(mnk)$. The space complexity for storing sensor relationships is $O(n^2)$, while the space complexity for storing the PageRank value of each sensor is $O(n)$.

The proposed approach (PA) consistently outperforms both the category-based (C) and category-and-function-area-based (CF) mapping approaches. Additionally, the performance is significantly enhanced when using BN as the classifier across both groups, achieving the best average precision and accuracy.

4.4. Discussion

The experimental results demonstrate that the proposed approach consistently achieves better performance. Importantly, variations between datasets do not significantly impact the recognition accuracy, which suggests that the proposed model can be applied in a wide range of scenarios.

The advantages of the proposed approach can be attributed to two key factors. Clustering Sensors by Significance Degree: By clustering sensors based on their significance degrees, the feature space of daily activities is effectively optimized. This optimization helps in distinguishing instances of daily activities more precisely, thereby improving the recognition accuracy. Optimized Mapping Between Clusters: Algorithm 2 plays a crucial role in finding an optimized mapping between clusters. This enables the model to more accurately map sensors from different smart homes, enhancing the overall performance of the system.

5. Conclusions

This paper introduces a novel fine sensor mapping approach, which leverages the PageRank algorithm to determine the significance degrees of sensors and subsequently refines the feature space for daily activity recognition. Based on this, an exact alignment algorithm is proposed to achieve accurate sensor mapping. The effectiveness of the proposed method is evaluated using six datasets, and the results demonstrate its superior performance in terms of precision and accuracy.

Sensor mapping is a critical challenge in Daily Activity Recognition (DAR). The proposed approach proves to be effective in smart homes with similar or identical layouts. However, for heterogeneous smart homes, specialized sensor mapping approaches are still needed. In future work, we aim to combine Deep Subdomain Adaptation Networks to enhance sensor mapping between heterogeneous smart homes. Moreover, the proposed approach is validated under the assumption of sensor uniformity to establish a baseline for performance evaluation. However, in real-world scenarios, variations in sensor characteristics can introduce uncertainties. In future work, we plan to incorporate additional

robustness measures, such as preprocessing techniques, adaptive calibration, and statistical compensation, to assess the algorithm's performance under varying sensor conditions. We also aim to explore strategies that could enhance its adaptability.

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References

1. Bhalotia, N.; Kumar, M.; Alameen, A.; Mohapatra, H.; Kolhar, M. A Helping Hand to the Elderly: Securing Their Freedom through the HAIE Framework. *Appl. Sci.* **2023**, *13*, 6797. [\[CrossRef\]](#)
2. Cook, D.J.; Duncan, G.; Sprint, G.; Fritz, R.L. Using Smart City Technology to Make Healthcare Smarter. *Proc. IEEE* **2018**, *106*, 708–722. [\[CrossRef\]](#)
3. Yan, S.; Lin, K.-J.; Zheng, X.; Zhang, W. Using latent knowledge to improve real-time activity recognition for smart IoT. *IEEE Trans. Knowl. Data Eng.* **2020**, *32*, 574–587. [\[CrossRef\]](#)
4. Chen, L.M.; Hoey, J.; Nugent, C.D. Sensor-Based Activity Recognition. *IEEE Trans. Syst. Man Cybern. Part C Appl. Rev.* **2012**, *42*, 790–808. [\[CrossRef\]](#)
5. Wu, C.-L.; Chen, Y.-H.; Chien, Y.-W.; Tsai, M.-J.; Li, T.-Y.; Cheng, P.-H.; Fu, L.-C.; Chen, C.C.-H. Nonparametric Activity Recognition System in Smart Homes Based on Heterogeneous Sensor Data. *IEEE Trans. Autom. Sci. Eng.* **2019**, *16*, 678–690. [\[CrossRef\]](#)
6. Yu, Y.; Hao, Z.; Li, G.; Liu, Y.; Yang, R.; Liu, H. Optimal search mapping among sensors in heterogeneous smart homes. *Math. Biosci. Eng.* **2023**, *20*, 1960–1980. [\[CrossRef\]](#)
7. Klietstik, T.; Nica, E.; Durana, P.; Popescu, G.H. Artificial intelligence-based predictive maintenance, time-sensitive networking, and big data-driven algorithmic decision-making in the economics of Industrial Internet of Things. *Oeconomia Copernic.* **2024**, *14*, 1097–1138. [\[CrossRef\]](#)
8. Andronie, M.; Lăzăroiu, G.; Karabolevski, O.L.; Ștefănescu, R.; Hurloiu, I.; Dijmărescu, A.; Dijmărescu, I. Remote Big Data Management Tools, Sensing and Computing Technologies, and Visual Perception and Environment Mapping Algorithms in the Internet of Robotic Things. *Electronics* **2022**, *12*, 22. [\[CrossRef\]](#)
9. Lazaroiu, G.; Androniceanu, A.; Grecu, I.; Grecu, G.; Neguriță, O. Artificial intelligence-based decision-making algorithms, Internet of Things sensing networks, and sustainable cyber-physical management systems in big data-driven cognitive manufacturing. *Oeconomia Copernic.* **2022**, *13*, 1047–1080. [\[CrossRef\]](#)
10. Deng, W.; Chen, X.; Li, X.; Zhao, H. Adaptive Federated Learning With Negative Inner Product Aggregation. *IEEE Internet Things J.* **2024**, *11*, 6570–6581. [\[CrossRef\]](#)
11. Zhao, H.; Wu, Y.; Deng, W. An Interpretable Dynamic Inference System Based on Fuzzy Broad Learning. *IEEE Trans. Instrum. Meas.* **2023**, *72*, 1–12. [\[CrossRef\]](#)
12. Wang, W.; Li, J.; Li, Y.; Dong, X. Predicting Activities of Daily Living for the Coming Time Period in Smart Homes. *IEEE Trans. Hum.-Mach. Syst.* **2023**, *53*, 228–238. [\[CrossRef\]](#)
13. Samarah, S.; AL Zamil, M.G.; Rawashdeh, M.; Hossain, M.S.; Muhammad, G.; Alamri, A. Transferring Activity Recognition Models in FOG Computing Architecture. *J. Parallel Distrib. Comput.* **2018**, *122*, 122–130. [\[CrossRef\]](#)
14. Chiang, Y.-T.; Lu, C.-H.; Hsu, J.Y.-J. A Feature-Based Knowledge Transfer Framework for Cross-Environment Activity Recognition Toward Smart Home Applications. *IEEE Trans. Hum. Mach. Syst.* **2017**, *47*, 310–322. [\[CrossRef\]](#)
15. Hamad, R.A.; Kimura, M.; Yang, L.; Woo, W.L.; Wei, B. Dilated causal convolution with multi-head self attention for sensor human activity recognition. *Neural Comput. Appl.* **2021**, *33*, 13705–13722. [\[CrossRef\]](#)
16. Wang, K.; Saragadam, A.; Kaur, J. A contactless method for recognition of daily living activities for older adults based on ambient assisted living technology. *Internet of Things* **2025**, *30*. [\[CrossRef\]](#)
17. Wan, J.; O'grady, M.J.; O'Hare, G.M. Gregory. Dynamic Sensor Event Segmentation for Real-Time Activity Recognition in a Smart Home Context. *Pers. Ubiquitous Comput.* **2015**, *19*, 287–301. [\[CrossRef\]](#)
18. Aminikhanghahi, S.; Cook, D.J. Enhancing Activity Recognition Using CPD-Based Activity Segmentation. *Pervasive Mob. Comput.* **2019**, *53*, 75–89. [\[CrossRef\]](#)

19. Aminikhanghahi, S.; Wang, T.; Cook, D.J. Real-Time Change Point Detection with Application to Smart Home Time Series Data. *IEEE Trans. Knowl. Data Eng.* **2019**, *31*, 1010–1023. [\[CrossRef\]](#)
20. Wen, J.; Zhong, M.; Wang, Z. Activity Recognition with Weighted Frequent Patterns Mining in Smart Environments. *Expert Syst. Appl.* **2015**, *42*, 6423–6432. [\[CrossRef\]](#)
21. Nasreen, S.; Azam, M.A.; Naeem, U.; Ghazanfar, M.A.; Khalid, A. Recognition Framework for Inferring Activities of Daily Living Based on Pattern Mining. *Arab. J. Sci. Eng.* **2016**, *41*, 3113–3126. [\[CrossRef\]](#)
22. Malazi, H.T.; Davari, M. Combining Emerging Patterns with Random Forest for Complex Activity Recognition in Smart Homes. *Appl. Intell.* **2018**, *48*, 315–330. [\[CrossRef\]](#)
23. Guo, J.; Mu, Y.; Xiong, M.; Liu, Y.; Gu, J. Activity Feature Solving Based on TF-IDF for Activity Recognition in Smart Homes. *Complexity* **2019**, *2019*, 5245373. [\[CrossRef\]](#)
24. Yala, N.; Fergani, B.; Fleury, A. Towards Improving Feature Extraction and Classification for Activity Recognition on Streaming Data. *J. Ambient. Intell. Humaniz. Comput.* **2017**, *8*, 177–189. [\[CrossRef\]](#)
25. Gochoo, M.; Tan, T.-H.; Liu, S.-H.; Jean, F.-R.; Alnajjar, F.S.; Huang, S.-C. Unobtrusive activity recognition of elderly people living alone using anonymous binary sensors and DCNN. *IEEE J. Biomed. Health Inform.* **2018**, *23*, 693–702. [\[CrossRef\]](#)
26. Ghods, A.; Cook, D.J. Activity2vec: Learning adl embeddings from sensor data with a sequence-to-sequence model. *arXiv* **2019**, arXiv:1907.05597.
27. Bouchabou, D.; Nguyen, S.M.; Lohr, C.; LeDuc, B.; Kanellos, I. Fully Convolutional Network Bootstrapped by Word Encoding and Embedding for Activity Recognition in Smart Homes. In Proceedings of the IJCAI 2020 Workshop on Deep Learning for Human Activity Recognition, Yokohama, Japan, 7–15 January 2021.
28. Alshammari, T.; Alshammari, N.; Sedky, M.; Howard, C. Evaluating machine learning techniques for activity classification in smart home environments. *Int. J. Inf. Commun. Eng.* **2018**, *12*, 48–54.
29. Rodríguez-Gallego, C.; Díez-Muñoz, F.; Martín-Ruiz, M.-L.; Gabaldón, A.-M.; Dolón-Poza, M.; Pau, I. A Collaborative Semantic Framework Based on Activities for the Development of Applications in Smart Home Living Labs. *Futur. Gener. Comput. Syst.* **2023**, *140*, 450–465. [\[CrossRef\]](#)
30. Deng, W.; Cai, X.; Wu, D.; Song, Y.; Chen, H.; Ran, X.; Zhou, X.; Zhao, H. MOQEA/D: Multi-objective QEA with decomposition mechanism and excellent global search and its application. *IEEE Trans. Intell. Transp. Syst.* **2024**, *25*, 12517–12527. [\[CrossRef\]](#)
31. Chen, H.; Long, H.; Chen, T.; Song, Y.; Chen, H.; Zhou, X.; Deng, W. M3FuNet: An Unsupervised Multivariate Feature Fusion Network for Hyperspectral Image Classification. *IEEE Trans. Geosci. Remote Sens.* **2024**, *62*, 1–15. [\[CrossRef\]](#)
32. Deng, W.; Li, K.; Zhao, H. A Flight Arrival Time Prediction Method Based on Cluster Clustering-Based Modular With Deep Neural Network. *IEEE Trans. Intell. Transp. Syst.* **2024**, *25*, 6238–6247. [\[CrossRef\]](#)
33. Li, X.; Zhao, H.; Deng, W. IOFL: Intelligent-Optimization-Based Federated Learning for Non-IID Data. *IEEE Internet Things J.* **2024**, *11*, 16693–16699. [\[CrossRef\]](#)
34. Lu, L.; Cai, Q.; Zhan, Y. Activity Recognition in Smart Homes. *Multimed. Tools Appl.* **2017**, *76*, 24203–24220. [\[CrossRef\]](#)
35. Fahad, L.G.; Rajarajan, M. Integration of Discriminative and Generative Models for Activity Recognition in Smart Homes. *Appl. Soft Comput.* **2015**, *37*, 992–1001. [\[CrossRef\]](#)
36. Tong, Y.; Chen, R. Latent-Dynamic Conditional Random Fields for Recognizing Activities in Smart Homes. *J. Ambient. Intell. Smart Environ.* **2014**, *6*, 39–55. [\[CrossRef\]](#)
37. Hu, C.; Chen, Y.; Hu, L.; Peng, X. A Novel Random Forests Based Class Incremental Learning Method for Activity Recognition. *Pattern Recognit.* **2018**, *78*, 277–290. [\[CrossRef\]](#)
38. Krawczyk, B. Active and Adaptive Ensemble Learning for Online Activity Recognition from Data Streams. *Knowl. Based Syst.* **2017**, *138*, 69–78. [\[CrossRef\]](#)
39. Jurek, A.; Nugent, C.; Bi, Y.; Wu, S. Clustering-Based Ensemble Learning for Activity Recognition in Smart Homes. *Sensors* **2014**, *14*, 12285–12304. [\[CrossRef\]](#) [\[PubMed\]](#)
40. Hao, J.; Bouzouane, A.; Gaboury, S. Recognizing Multi-Resident Activities in Non-Intrusive Sensor-Based Smart Homes by Formal Concept Analysis. *Neurocomputing* **2018**, *318*, 75–89. [\[CrossRef\]](#)
41. Singh, D.; Merdivan, E.; Psychoula, I.; Kropf, J.; Hanke, S.; Geist, M.; Holzinger, A. Human activity recognition using recurrent neural networks. In Proceedings of the International Cross-Domain Conference for Machine Learning and Knowledge Extraction, Reggio, Italy, 29 August–1 September 2017.
42. Chen, L.; Nugent, C.D.; Wang, H. A Knowledge-driven approach to activity recognition in smart homes. *IEEE Trans. Knowl. Data Eng.* **2012**, *24*, 961–974. [\[CrossRef\]](#)
43. Rodríguez, N.D.; Cuéllar, M.P.; Lilius, J.; Calvo-Flores, M.D. A Fuzzy Ontology for Semantic Modelling and Recognition of Human Behavior. *Knowl. Based Syst.* **2014**, *66*, 46–60. [\[CrossRef\]](#)
44. Noor, M.H.M.; Salcic, Z.; Wang, K.I.-K. Enhancing Ontological Reasoning with Uncertainty Handling for Activity Recognition. *Knowl. Based Syst.* **2016**, *114*, 47–60. [\[CrossRef\]](#)

45. Gayathri, K.; Easwarakumar, K.; Elias, S. Probabilistic Ontology Based Activity Recognition in Smart Homes Using Markov Logic Network. *Knowl. Based Syst.* **2017**, *121*, 173–184. [[CrossRef](#)]
46. Civitarese, G.; Szttyler, T.; Riboni, D.; Bettini, C.; Stuckenschmidt, H. POLARIS: Probabilistic and Ontological Activity Recognition in Smart-Homes. *IEEE Trans. Knowl. Data Eng.* **2021**, *33*, 209–223. [[CrossRef](#)]
47. Wen, J.; Zhong, M. Activity discovering and modelling with labelled and unlabelled data in smart environments. *Expert Syst. Appl.* **2015**, *42*, 5800–5810. [[CrossRef](#)]
48. Sukor, A.S.A.; Zakaria, A.; Rahim, N.A.; Kamarudin, L.M.; Setchi, R.; Nishizaki, H. A hybrid approach of knowledge-driven and data-driven reasoning for activity recognition in smart homes. *J. Intell. Fuzzy Syst.* **2019**, *36*, 4177–4188. [[CrossRef](#)]
49. Feuz, K.D.; Cook, D.J. Transfer learning across feature-rich heterogeneous feature spaces via feature-space remapping (FSR). *ACM Trans. Intell. Syst. Technol.* **2015**, *6*, 1–27. [[CrossRef](#)]
50. Azkune, G.; Almeida, A.; Agirre, E. Cross-environment activity recognition using word embeddings for sensor and activity representation. *Neurocomputing* **2020**, *418*, 280–290. [[CrossRef](#)]
51. Ye, J.; Dobson, S.; Zambonelli, F. XLearn: Learning Activity Labels across Heterogeneous Datasets. *ACM Trans. -Telligent Syst. Technol.* **2020**, *11*, 1–28. [[CrossRef](#)]
52. Wemlinger, Z.E.; Holder, L.B. Cross-Environment Activity Recognition Using a Shared Semantic Vocabulary. *Pervasive Mob. Comput.* **2018**, *51*, 150–159. [[CrossRef](#)]
53. Hu, D.H.; Yang, Q. Transfer learning for activity recognition via sensor mapping. In Proceedings of the Twenty-Second International Joint Conference on Artificial Intelligence, Catalonia, Spain, 16–22 July 2011; pp. 1962–1967.
54. Myagmar, B.; Li, J.; Kimura, S. Heterogeneous daily living activity learning through domain invariant feature subspace. *IEEE Trans. Big Data* **2021**, *7*, 922–929. [[CrossRef](#)]
55. Sun, H.; Wei, Y. A note on the PageRank algorithm. *Applied Mathematics and Computation* **2006**, *179*, 799–806. [[CrossRef](#)]
56. Cook, D.J.; Crandall, A.S.; Thomas, B.L.; Krishnan, N.C. CASAS: A smart home in a box. *Computer* **2013**, *46*, 62–69. [[CrossRef](#)]
57. Weka 3.8. Available online: <https://sourceforge.net/projects/weka/> (accessed on 29 April 2016).

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