Transfer Learning in Smart Home Scenario

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***Abstract*—With the development in sensor technology ambiance of human beings are becoming intelligent to cater to the needs and enhance their living standards. As human is dynamic in nature; therefore, a solution should be tailored to the needs of an individual. This requires the capability to understand, analyze and learn the behavior of a human being. To learn human behavior, machine learning algorithms require a sufficient amount of training data. Collection of data and labeling data consumes an ample amount of time. Also, it is not possible to collect data in every possible scenario. To deal with the mentioned problem, in the paper the concept of Transfer learning has been leveraged. The foremost requirement is to calculate the similarity and differences between a selected source domain and a target domain. For the calculation of similarities and differences, multiple parameters are defined in this paper. Multiple experiments in different scenarios were carried out to support the proposed approach. Results obtained show the effects of transfer learning in the domain of smart homes.**

***Index Terms*—Transfer Learning, Smart Homes, Machine Learning**

I. INTRODUCTION

Research in the domain of ubiquitous sensing, to sense the behaviour trends of a human being is at a mature stage. However, this requires a sufficient amount of training data. The research is challenging because every human being is different, so are their varying needs. Therefore, a proposed solution should be tailored to an individual. As per conventional approaches, the realization of an individual-specific solution requires a substantial amount of data which is a challenging task. Therefore, for such a solution, first, all the sensors should be in place to collect the training data for an individual human being. For example, let us assume that an activity recognition module is in place in a smart home, and this module is well trained using data of the current residents. However, in such a scenario if a new resident starts residing, the prior trained activity module might not provide desired results. To the mentioned problem, one of the possible solutions is to collect data for the new residents and re-train the module. A better alternative is to design a system that can leverage the previous knowledge for the performance improvement of the current task.

Human beings have the mental capability to use the previously gained knowledge to perform a new task which is never encountered before. Over the last decade, researchers are struggling to make an intelligent machine to match human brain capabilities which can leverage the experience into the performance of a newly assigned task. When the experience of the old task(s) is utilized to solve a new problem, this is considered to be *Transfer Learning (TL)*. The concept of transfer learning is useful in case of insufficient or no data. To implement this concept knowledge from source domain can be utilized in the target domain. However, it depends upon the similarity between the source domain and the target domain.

In the particular case of smart homes, the concept of transfer learning can be explored to set up a new house. The experience gained from the already running smart homes can be utilized to predict the sensors reading in the new house. This concept wave off the time required by conventional approaches for the collection of training data. Cook et al. [1] presented a survey on transfer learning for the activity recognition where the authors emphasize the challenge of calculation of similarity between the source domain and the target domain. The level of similarity between the source domain and target domain is dependent on a number of sensors, amount of the data in the source domain, modality of the sensors, the relative placement of sensors, etc. Specific to the domain of smart homes, transfer learning depends on the amount of labelled data available in the source domain. Unlike this, in other domains, researchers are successful to use the concept of TL by leveraging the unlabeled source data to make improvements in the target domain [1] [2].

As the applicability of transfer learning, two natural questions related to transfer learning arise. First, can a generalized method can be proposed to calculate the difference between the source and target populations? To calculate the differences, some domain-specific distances have been proposed in the past. However, those can be applied while working in a particular domain. While defining a generalized method to calculate the differences between a source domain and target domain need to indicate differences in term of feature spaces, temporal spaces, label spaces, etc. This measure can provide comparisons between various TL approaches and can indicate whether TL can be applied to a given situation. Second, can we detect and prevent the occurrence of negative transfer effects? TL can also degrade performance instead of increasing performance. Above two points are related to each other, because an accurate distance metric may provide an indication of the effects of transfer learning.

II. LITERATURE SURVEY

The area of transfer learning addresses the problems when there is insufficient or no training data, for example, a scenario

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where a new person enters a house, initially, there is no or insufficient data corresponding to his activities. In the case of lacking data, it is difficult to predict the behaviour of the new entry. To cater to this problem, Transfer Learning (TL) is adopted by the researchers for a system to be flexible to support a new entry. Inspired by human intelligence, transfer learning can be defined as an ability to identify the deep, subtle connection between two contexts/domains/tasks. Transfer Learning term is first used by Thorndike and Woodworth [3]. Researchers [4] focused on the development of Transfer Learning algorithms to reduce labelling efforts. This requires a transfer of useful knowledge from the source domain to the target domain where training data is insufficient, which holds true when a new user enters in a multi-resident space. The concept of transfer learning for activity recognition has been successfully applied to set up a new smart environment in [5]. The concept of transfer learning is used by researchers [6] [7] [1] in the field of activity recognition data collected using vision-based sensors. However, processing the data of vision-based sensors raises issues related to the privacy concerns of the people in the source domain.

The knowledge is transferred from the houses where ample amount of labelled sensory data for each activity is available. Researchers have successfully applied the concept of TL within the sensors of the same modality. However, the problem of cross-modality transfer learning is still a challenging problem to solve. Kurz et al. [8] propose a student/learner model to address the problem of transfer learning in cross sensor modality domains. Similarly, to cater to the similar problem Hu et al. [6] proposed a transfer learning approach. However, the concept of transfer learning to predict and analyze the activity routine for health and wellness detection using unlabeled data is new. Work focusing on transferring across difference in time [9] [10] [11], human difference [12] [13] [14] [15], and devices difference [16] [17] has been published. Transfer learning does not limit the number of resources. Therefore, the number of sources can vary from single to multiple. Because of the involvement of physical settings, finding a relation between the source domain and the target domain is harder as compared to other domains. In this domain, type of sensors used, placement of sensors, number of sensors, how a human being performs an activity also plays a vital role in the calculation of similarity between a source domain and a target domain [1]. One of the first sensors which is used to learn the activities of a human being is a video camera. Based on the data received, the similarities between a source domain and target domain are calculated using Spatio-temporal features [18]. However, this sensor invades into the privacy of a human being. Also, for a camera to track a person, its position, angle of orientation also affect the collection of data pertaining to the activities of human beings [19]. Similarly, wearable sensors and non-intrusive sensors are also used to capture the data for the activities of a human being [20]. The sampling rate, sensor modalities can be considered as spatial features which can be further used to calculate the differences and similarity between the source and the target domains. At the same time, apart from spatial features, temporal features, sensor types, labels and devices cannot be neglected to calculate the similarity between a source and a target domain [1]. As compared to other considered factors, the amount of labelled data and transferring the knowledge across different labels has gained the attention of researchers [12] [20]. However, the question arises whether transfer learning can be performed using unlabeled data, which is being discussed in this paper. The proposed approach relies on the representation of data in a vector form in such a way that labelling is not required. It can possibly give output in terms of time, sensors active and active sensors location. The same representation has been exploited for transfer learning, where data is not available.

One of the most accepted work for transfer learning in activity recognition is Teacher/Learning TL [1]. As per proposed approach, earlier trained model work in parallel with a new model where the old model provides labels to train the new model. The mentioned approach requires sufficient amount of labelled data to train the Teacher (old) model. Two different types known as *inductive* and *transductive* learning are defined by Pan and Yang [2] for TL techniques. As explained by researchers, in inductive learning, knowledge is transferred regarding model parameters and predictive functions. On the other hand, in transductive learning, knowledge of data instance is transferred to the target domain. However, most of the work in this area leverage the amount of labelled data to calculate the distance between a source domain and a target domain. Despite the abundance of work in this domain, research which is built on the unlabeled data in the source domain is very sparse.

III. PROBLEM DEFINITION

Let S_r denotes source domain and T_g denotes target domain. S_r is well equipped with multiple sensors placed at different locations. The data received from different embedded sensors is used to train a particular algorithm which is implemented to predict the future routine of a person. S has sufficient amount of training data which is collected over months. However, T_g is also equipped with similar sensors but its layout and its resident is different from S_r. Also, T_g lacks in amount of training data. Now, the challenge is to find a way in which the knowledge gained in S_r can be reused in T_g. In other words, how the learning of the source domain can be transferred to the target domain. Knowledge can be values of parameters, machine learning model, raw data, processed data, etc. Let Tg_{prm} denotes the parameters in the target domain and Sr_{prm} denotes the parameters in source domain. So, the problem can be formally defined as :

$$Tg_{prm} \alpha_r Sr_{prm} \tag{1}$$

where, α_r represents the relation between parameters of the target domain and the source domain. Knowledge of the parameters Sr_{prm} of source domain is available. Challenge is to find the relation between source domain and target domain that is α_r and then using that similarity to determine the value of Tg_{prm} by leveraging the knowledge of Sr_{prm}.

IV. PROPOSED APPROACH

Conventional intelligent systems that are designed to cater to the needs of a human being requires information related to different activities performed by him. An activity recognition algorithm relies on training data and yet need improvisation to perform well under diverse circumstances. Labelling a data set consumes many man-hours, and it is difficult to get a substantial amount of labelled data in every possible scenario. Researchers are focusing on designing a generalized similarity matrix to find a relation between two different data sets and to perform transfer learning to solve the problem of insufficient/no data issue. Using transfer learning knowledge obtained from a source domain can be transferred to a target domain. Transfer learning is about finding the relevant source data set. One of the challenges in Transfer Learning is to find a compatible source data-set. When this source data-set has been recognized, its relating model parameters can be utilized for transfer learning. However, in the case of smart houses, structural likenesses of the living spaces and the number of residents can be useful criteria. The structural likeliness can be measured by maintaining a count of the number of sensors, living room, kitchen, washroom, number of smart devices, floor map, etc. Even though limiting the scope to activity recognition, it is unfeasible to calculate all the possible differences between the source domain and target domain. In the domain of pattern recognition and behaviour analysis of a human being, there can be differences across time, people, devices, data sampling rate, sensor modalities, etc. These differences need to be considered while calculating the similarities between a source domain and a target domain. Unlike conventional approaches, the proposed approach in this paper does not require labelled data, thus saves time and effort required to label the data.

A. Data Representation

Sensors are embedded in the living space of human beings to collect data for human activities. Sensory data is stored and labelled manually. For the proposed approach, the routine of a human being is represented in a vector form. Let, a vector $\mathcal{V}$ represents the one day routine of a human being. A routine is defined as the sequence of sensory data collected from various embedded sensors for 24 hours. A vector $\mathcal{V}$ is divided into subvectors. A subvector consists of data received from all the embedded sensors at a given time instance 't'. If data is stored in seconds, then it can be inferred that V has a sequence of $24 * 60 * 60$ subvectors. The dimension of a subvector is equal to the number of embedded sensors in the living space of a human being. Figure 1 shows the structure of a vector and subvectors.

B. Similarity Matrix

Transfer Learning is about finding a matching source domain. Depending on the similarity between a source domain and a target domain, performance in the target domain using TL can be improved to high extends. Depending on the choice of the source domain, transfer learning can also affect the performance of the target domain negatively. In the domain of smart homes where apart from the data patterns and its features, sensors types, their modalities, their physical placement and how a human being performs an activity, it becomes a challenge to find the similarity between a source domain and a target domain. For obvious reasons, smart homes are tailored to the needs of an individual human being. Being a dynamic creature, every human being has a different way to perform a given activity, which is difficult to capture and relate to another human being. Several parameters [1] [3] are defined by researchers to calculate the similarity between the source domain and the target domain. Solutions being proposed by researchers [1] are dependent on the amount of labelled data in the source domain, which further add complexity to the problem. Unlike conventional approaches, the proposed approach in this paper is independent of labelled data because it relies on the vector representation of the sensory data, as explained in the data representation section. Following are the certain parameters that are later explained to calculate the similarity between a source domain and a target domain.

Knowledge can be transferred in two ways:// 1. Inter-House transfer// 2. Intra-House transfer

C. Inter House Knowledge Transfer

Inter-house knowledge transfer can be referred to a transfer the knowledge of the activities of a resident of a house to train a model built for another person residing in another house. However, one of the challenges in Transfer Learning is to find a compatible source data-set. When this source data-set has been recognized, its relating model (LSTM) can be utilized for transfer learning. However, in the case of smart houses, structural likenesses of the living spaces and the number of residents can be a useful criterion. The structural likeliness can be measured by maintaining a count of the number of sensors, living room, kitchen, washroom, number of smart devices, floor map, etc. Even though limiting the scope to activity recognition, it is not feasible to calculate all the possible differences between the source domain and target domain.

1) Sensor Modality and Physical Space (α_1): Sensor modalities are one of the essential factors to be considered for transfer-learning techniques. Some techniques may be generalized to sensor modalities, but some techniques are too specific for sensor modalities depending on the application. One of such applications is activity recognition where the difference in sensor modalities infer the differences between source and target domain. This, in turn, effect the knowledge that is transferred from the source domain to the target domain. Thus, physical settings of a space are essential for the domain of activity recognition. To enumerate the differences between a source and a target domain in terms of sensor modality and physical space settings, we define a term *paired sensors*. Two sensors S_i in a target domain and S_j in a source domain, are

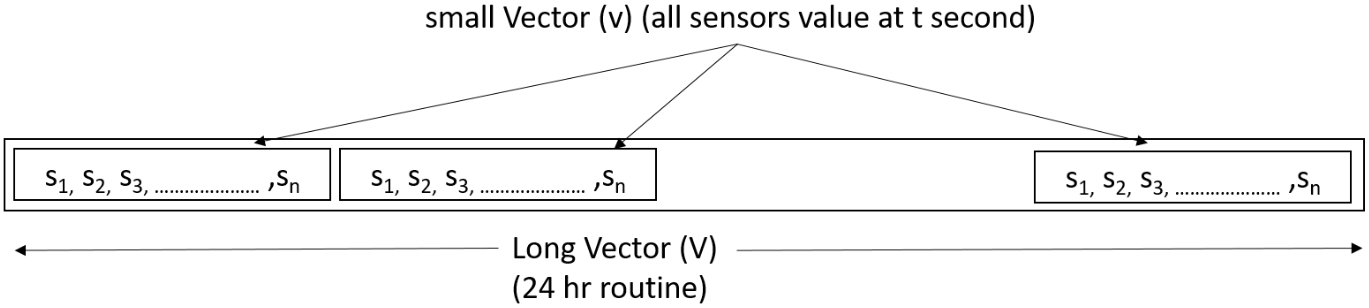


Fig. 1. Vector representation of data

said to be *Paired* iff they have the same modality and possess the same physical settings. For example, there is a PIR sensor (S_1) embedded at the door of a kitchen situated in a source domain to detect the movement in that area. Similarly, there is a PIR or similar sensor (which can sense the motion of a human) S_2 at the door of a kitchen in a target domain. The sensors in both domains are located at the entrance of a kitchen and serve the same purpose, that is the detection of human (movement) in that particular area. Therefore as per the definition of paired sensors S_1 and S_2 are paired sensors.

Enumeration of the differences between a source and a target domain in terms of sensor modality and physical space is dependent on :

1. **Number of paired sensors in target domain:**$|\chi_t| - |\chi_{s_i}|$ Higher the number of paired sensors in a target domain, high will be the similarity between a target domain and a source domain.
2. **Number of unpaired sensors in target domain and source domain:** Corresponding to the unpaired sensors in the source domain there is no sensor in the target domain to capture the similar kind data (or activity). Therefore, learning from the data of unpaired sensors in the source domain cannot be utilized in the target domain. Therefore higher the number of unpaired sensors in both the source and the target domain, lesser will be the similarity between source and target domain.
3. **Difference in the total number of sensors placed in a source domain and a target domain:** Total count of sensors and their respective placements are important to find the most compatible source domain for transfer learning. The difference in the placement of sensors reflects the difference in the data collected for the same activity. Thus, lowering the similarity between source domain and the target domain.

Combining the above points all together α_1 is calculated by equation 2.

$$\alpha_1 = \frac{|(\chi_t \cap \chi_{s_i}|}{|\chi_t|} - \frac{|\chi_t - \chi_{s_i}| + |\chi_{s_i} - \chi_t|}{|\chi_t|} + \frac{|\chi_t|}{(|\chi_t| - |\chi_{s_i}|)} \tag{2}$$

where $|(\chi_t \cap \chi_{s_r}|$:Number of paired sensors in a target domain.

$|\chi_t - \chi_{s_r}| + |\chi_{s_r} - \chi_t|$:Number of unpaired sensors in a target and a source domain.

$|\chi_t|$: Total number of sensors in a target domain.

$|\chi_t| - |\chi_{s_r}|$: Difference in the number of sensors in a target domain and number of sensors in a source domain.

2) Number of residents and Data Sampling Rate (α_2): TL can be performed between multi-resident and single resident spaces or between multi-resident spaces. In these cases data sampling rate is an important factor to be considered to calculate the difference between a source domain and a target domain. If the sampling frequency of a source and a target domain matches, then cosine similarity between the routine of the residents of the source domain and target domain is calculated. Difference in the sampling rate of a source domain and a target domain leads to low efficiency of TL. To normalize the difference below is the equation to calculate the value of α_3. Corresponding to the calculated cosine similarity, α_2 can be calculated as:

$$\alpha_2 = \frac{\sum fq_{s_r}^{s_k} - \sum fq_{fq_t}^{s_k}}{\sum fq_{s_r}^{s_k}} \tag{3}$$

Where $fq_{s_r}^{s_k}$ is the sampling frequency of k^{th} sensor in a source domain and $fq_{f_t}^{s_k}$ is the sampling frequency of k^{th} in a target domain.

3) Deviation in routines α_3: Conventional machine learning algorithms use either supervised or unsupervised machine learning. However, in case of TL in the domain of activity recognition and prediction, data can be either labeled or unlabeled. With the labeled data , relationship between two instances can be learned which is difficult to learn with unlabelled data. In case of unlabelled data α_3 is defined, which calculates the average deviation in the routine of a human being in a source domain. On the basis of average deviation between daily routines this factor helps to improve the build model.

$$\alpha_3 = \frac{1}{N} \sum Cosine(R_{s_{r_i}})(R_{s_{r_j}}) \tag{4}$$

D. Intra-house Transfer Learning (α_4)

In a house, it is one of the probable cases that a person moves out of the house and a new person replaces him. In this case, data for the previous resident is available. However, there is no data for the new resident. In this particular scenario, number of sensors, data sampling rate, physical settings are same except the resident. This scenario refers to the the case of intra-house Transfer Learning where the knowledge of the old resident can be leveraged to build a model for a new resident. Below is the equation to calculate α_4:

$$\alpha_4 = W_{old} \tag{5}$$

Where W_{old} is the weight matrix of the model trained for the old resident.

Also, in the case of a multi-resident scenario, the knowledge can be transferred from its old residents to support a new entry in the house. In that particular scenario, below is the equation to calculate α_4

$$\alpha_4 = (\frac{1}{n-1}\sum_{i=1}^{(n-1)} \theta'_{ij}) \tag{6}$$

E. Relation between source and target domain

After, calculation of $\alpha_1, \alpha_2, \alpha_3, \alpha_4$, weights for the model to built a LSTM for a new comer can be defined as:

$$\begin{split}\alpha_{new} = \frac{1}{2}(\frac{1}{3}(\alpha_1 + \alpha_2 + \alpha_3)(W_x^{S_r}) \\ + \alpha_4(W_x^T))\end{split} \tag{7}$$

V. DATA COLLECTION

To collect the data, non-intrusive sensors are embedded in the living space of 50 oldage subjects. The sensors include PIR, Vibration sensor, Temperature and humidity sensor, water sensor, gas sensor, ultrasonic sensor, touch sensor, etc. In total 25 sensors are embedded to capture the daily routine of a human being. Sensors are placed at different locations to capture the data of different activities such as bed room, living room, kitchen, bathroom, etc. As shown in figure 2 data from different sensors is stored along with time. Data is stored every second. A complete set up for data collection is explained in figure 3. Sensors are connected with an arduino board to collect the data. Via gateway data is sent to the IoT middleware for the further analysis.

VI. EXPERIMENTS AND RESULTS

Different experiments were conducted to prove the efficacy of the proposed approach. Experiments were performed for different scenarios. In every scenario, the routine of a human being was defined in a structured manner as defined in the data representation section. The data dimension is too high, so to reduce the dimension encoder-decoder was utilized. For every human being in the source domain, an LSTM model was built. Six months of data was used to train the LSTM. Accuracy in the target domain is calculated from the data of three months. Different possible cases were considered to perform the experiments:

A. Case 1

For the first set of experiments, single residential houses were considered. We considered 20 houses for the first set of experiments. First, 10 houses were tagged as source domains, and another 10 houses were tagged as target domains. For each target house, similarity parameters as defined in the proposed approach were calculated. Based on the similarity parameters, knowledge were transferred from the source domain to the target domain. To quantify the results, the cosine similarity was calculated between predicted routines and the actual routine.

table in figure 4 shows the average of the accuracy calculated for every possible pair of a source domain and a target domain. In the source domain and the target domain, only single resident houses were considered. It can be depicted from the table in figure that approximately above 80, accuracy can be achieved by using the concept of transfer learning. In the table in figure, some low numbers are also present which agree with the statement that transfer learning can also affect performance negatively. It can be inferred from the table in figure, for domain $T1$, $S4$ is most matching source domain, and $S3$ is the domain which don't match at all. A low number in table in figure 4 for any combination of a source and target shows the lack of similarity between them.

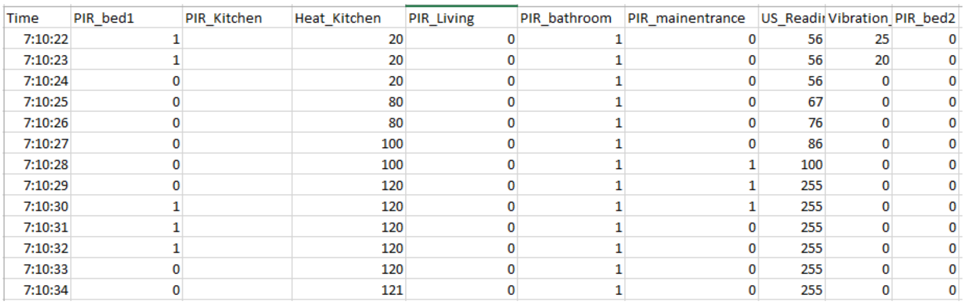
B. Case 2

For the second set of experiments, both single resident houses and multi-resident houses were considered. For this set of experiments, two multi-resident houses were tagged as the source domain, and 10 single resident houses were tagged as the target domain. Each multi-resident house had data of 3 members. Similarity parameters were calculated between each member of the multi-resident house and the target domain houses. Results are quantifying in the same way, as mentioned in case 1.

table in figure 5 shows the accuracy results obtained for scenarios where knowledge is transferred from a multi-resident house to a single resident house. In the table in figure in figure 5, for each target domain, maximum and minimum accuracy achieved is highlighted. Accuracy is calculated for every member in a multi-resident house. Similar to case 1, in this case also there are low numbers which indicate that knowledge can be transferred. For example, for target $T2$, knowledge of member number 2 from house number 2 cannot be utilized.

C. Case 3

The third set of experiments is opposite to case 2 experiments. For this set of experiments also both muti-resident and single resident houses were considered. But for this set of experiments, single residential houses were tagged as the source domain, and multi-resident houses were tagged as the target domain. Similar to case 2, 2 multi-resident houses were considered, and 10 single resident houses were considered. Each multi-resident house needed data for 3 members. For each member of the multi-resident houses, knowledge is transferred from a single resident house. For each member



Time	PIR_bed1	PIR_Kitchen	Heat_Kitchen	PIR_Living	PIR_bathroom	PIR_mainentrance	US_Readir	Vibration_	PIR_bed2
7:10:22	1		20	0	1	0	56	25	0
7:10:23	1		20	0	1	0	56	20	0
7:10:24	0		20	0	1	0	56	0	0
7:10:25	0		80	0	1	0	67	0	0
7:10:26	0		80	0	1	0	76	0	0
7:10:27	0		100	0	1	0	86	0	0
7:10:28	0		100	0	1	1	100	0	0
7:10:29	0		120	0	1	1	255	0	0
7:10:30	1		120	0	1	1	255	0	0
7:10:31	1		120	0	1	0	255	0	0
7:10:32	1		120	0	1	0	255	0	0
7:10:33	0		120	0	1	0	255	0	0
7:10:34	0		121	0	1	0	255	0	0

Fig. 2. A snapshot of data

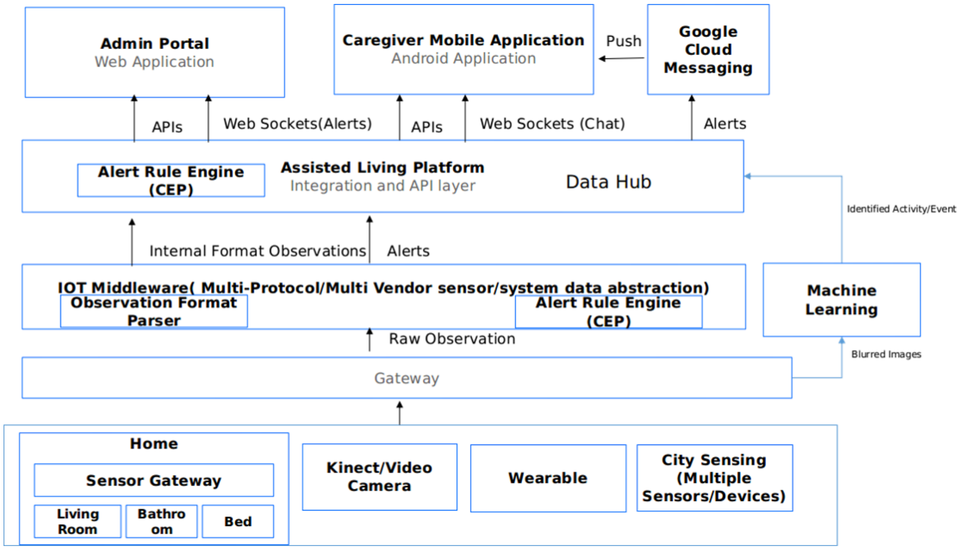
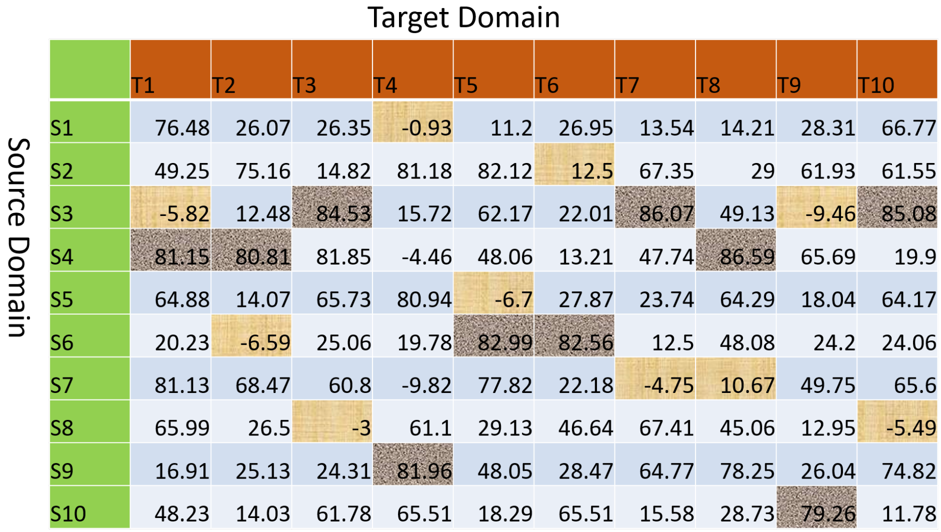


Fig. 3. Sensor Set-up



Target Domain

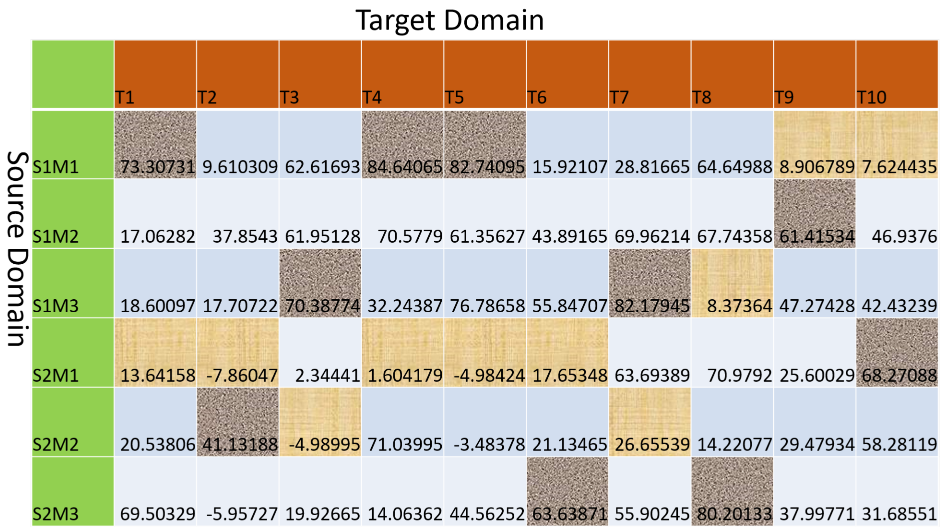
Source Domain

	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
S1	76.48	26.07	26.35	-0.93	11.2	26.95	13.54	14.21	28.31	66.77
S2	49.25	75.16	14.82	81.18	82.12	12.5	67.35	29	61.93	61.55
S3	-5.82	12.48	84.53	15.72	62.17	22.01	86.07	49.13	-9.46	85.08
S4	81.15	80.81	81.85	-4.46	48.06	13.21	47.74	86.59	65.69	19.9
S5	64.88	14.07	65.73	80.94	-6.7	27.87	23.74	64.29	18.04	64.17
S6	20.23	-6.59	25.06	19.78	82.99	82.56	12.5	48.08	24.2	24.06
S7	81.13	68.47	60.8	-9.82	77.82	22.18	-4.75	10.67	49.75	65.6
S8	65.99	26.5	-3	61.1	29.13	46.64	67.41	45.06	12.95	-5.49
S9	16.91	25.13	24.31	81.96	48.05	28.47	64.77	78.25	26.04	74.82
S10	48.23	14.03	61.78	65.51	18.29	65.51	15.58	28.73	79.26	11.78

Fig. 4. Average accuracy calculated for every pair of source domain and target domain

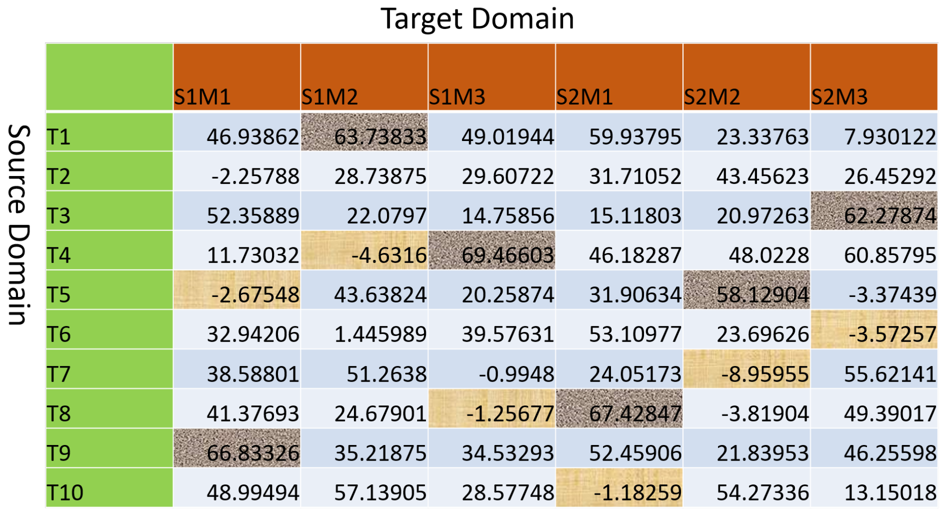
in the house, results are quantified using cosine similarity between the actual routine vectors and the predicted routine vectors.

Values presented in table in figure 6 shows the average accuracy obtained while transferring knowledge from a single resident house to a multi-resident houses.



	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
S1M1	73.30731	9.610309	62.61693	84.64065	82.74095	15.92107	28.81665	64.64988	8.906789	7.624435
S1M2	17.06282	37.8543	61.95128	70.5779	61.35627	43.89165	69.96214	67.74358	61.41534	46.9376
S1M3	18.60097	17.70722	70.38774	32.24387	76.78658	55.84707	82.17945	8.37364	47.27428	42.43239
S2M1	13.64158	-7.86047	2.34441	1.604179	-4.98424	17.65348	63.69389	70.9792	25.60029	68.27088
S2M2	20.53806	41.13188	-4.98995	71.03995	-3.48378	21.13465	26.65539	14.22077	29.47934	58.28119
S2M3	69.50329	-5.95727	19.92665	14.06362	44.56252	63.63871	55.90245	80.20133	37.99771	31.68551

Fig. 5. Average accuracy calculated for multi-resident source domain and single-resident target domain



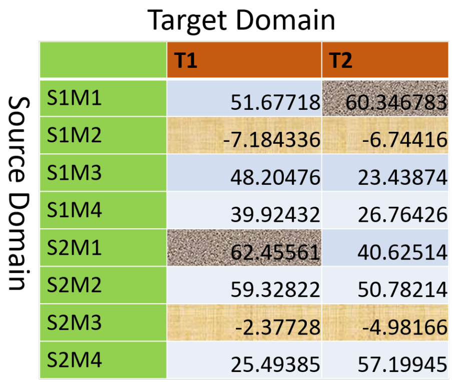
	S1M1	S1M2	S1M3	S2M1	S2M2	S2M3
T1	46.93862	63.73833	49.01944	59.93795	23.33763	7.930122
T2	-2.25788	28.73875	29.60722	31.71052	43.45623	26.45292
T3	52.35889	22.0797	14.75856	15.11803	20.97263	62.27874
T4	11.73032	-4.6316	69.46603	46.18287	48.0228	60.85795
T5	-2.67548	43.63824	20.25874	31.90634	58.12904	-3.37439
T6	32.94206	1.445989	39.57631	53.10977	23.69626	-3.57257
T7	38.58801	51.2638	-0.9948	24.05173	-8.95955	55.62141
T8	41.37693	24.67901	-1.25677	67.42847	-3.81904	49.39017
T9	66.83326	35.21875	34.53293	52.45906	21.83953	46.25598
T10	48.99494	57.13905	28.57748	-1.18259	54.27336	13.15018

Fig. 6. Average accuracy calculated where source is single resident and target is multi-resident house

D. *Case 4*

Fourth and the final set of experiments multi-resident houses were considered. For this set of experiments, to collect the data of human activities in smart houses, sensors were embedded in 4 smart-house setups. In small houses, 25 sensors and large houses, 35 sensors were embedded. A small house has one bedroom, one living room, one kitchen and one washroom. A large house has two bedrooms, one living room, one reading room, one kitchen and two washrooms. The sensors were embedded in different places to capture the different activities of a human being(s). The sensors that were embedded were PIR, US, Vibration sensor, Temperature and humidity sensor, water sensor, gas sensor, touch sensor. Sensory data is buffered at every second. Embedded sensors are non-intrusive to respect the privacy concerns of residents. Data was collected continuously for nine months. In house1 and house, 2 data was collected for 4 persons and in house 3, and 4 data was collected for 3 persons. However, one of the member in the house 2 and 4 entered in the house from 180^{th} day onwards. For this set of experiments, house 1 and house 2 were tagged as the source domain, and house 3 and house 4 were tagged as the target domain. Similarity parameters were calculated so as to transfer the knowledge from the source domain to the target domain so as to predict the routine of a new entry in the target domain. Knowledge is transferred from different members of the houses in the source domain for the new entry in the target domain. Results are quantified in the same as of previous cases.

Table in figure 7 shows the results obtained for transfer learning from multi-resident house to multi-resident house.



	T1	T2
S1M1	51.67718	60.346783
S1M2	-7.184336	-6.74416
S1M3	48.20476	23.43874
S1M4	39.92432	26.76426
S2M1	62.45561	40.62514
S2M2	59.32822	50.78214
S2M3	-2.37728	-4.98166
S2M4	25.49385	57.19945

Fig. 7. Average accuracy calculated where source and target both are multi-resident houses

For each of the target domain, the source domain whose knowledge gives maximum accuracy and minimum or low accuracy are highlighted.

VII. CONCLUSIONS

The concept of transfer learning is proposed by researchers to match the human brain capability of leveraging the old knowledge to complete the never encountered task. This is useful in cases of insufficient data or no data. However, it is dependent on finding a similar source domain from which knowledge can be transferred to the target domain. If choosing a domain which does not have similarity with the target domain can worsen the performance in a target domain. In this paper, we explored the application of transfer learning in the domain of smart homes. Pertaining to this domain, the earlier proposed work by researchers relies on the amount of labelled data in a source domain. In this paper, an approach has been proposed, which uses unlabeled data in the source domain. To calculate the similarity between a source domain and a target domain, different parameters were calculated. To prove the efficacy of the proposed approach, different experiments were performed. Experiments include cases of where knowledge is transferred from single resident houses to single resident houses, single resident to multi-resident houses and vice versa and multi-resident houses to multi-resident houses. As explained, both positive as well as the negative performance of transfer learning. However, the usage of transfer learning between different applications such as smart hospitals, smart offices, smart homes opens the research path for the future.

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