TransAct: Transfer Learning Enabled Activity Recognition

Md Abdullah Al Hafiz Khan
Department of Information Systems
University of Maryland, Baltimore County
Email: mdkhan1@umbc.edu

Nirmalya Roy
Department of Information Systems
University of Maryland, Baltimore County
Email: nroy@umbc.edu

***Abstract*—Activity recognition using smartphone has great potential in many applications like healthcare, obesity management, abnormal behavior detection, public safety and security etc. Typical activity detection systems are built on to recognize a limited set of activities that are present in the training and testing environments. However, these systems require similar data distributions, activity sets and sufficient labeled training data in both training and testing phases. Therefore, inferring new activities is challenging in practical scenarios where training and testing environments are volatile, data distributions are diverge and testing environment has new set of activities with limited training samples. The shortage of labeled training data samples also degrades the activity recognition performance. In this work, we address these challenges by augmenting the Instance based Transfer Boost algorithm with k-means clustering. We evaluated our TransAct model with three public datasets - HAR, MHealth and DailyAndSports and demonstrated that our TransAct model outperforms traditional activity recognition approaches. Our experimental results show that our TransAct model achieves $\approx$ 81% activity detection accuracy on average.**

I. Introduction

Recent progress in machine learning technology, mobile and wearable computing, and networking provides ample opportunities to handle the evolvability of various diverse context-aware applications. One of the important event monitoring application in smart home environments is human activity recognition. Smart home technologies help capture a multitude of sensing signals representing various context information of that environment. These information can easily be extracted by employing machine learning techniques which help decipher human behavioral information to develop various smart living applications.

Ubiquitous computing devices such as computer, smartphone, smart watch, smart necklace, tablet in our everyday living environments contain various in-built sensors such as accelerometer, gyroscope, light, audio, vision, GPS, heart rate etc. These miniaturized computing devices have the capability of sending and receiving data through various wireless medium such as Bluetooth, WiFi, Zigbee etc. Among these diverse sensors of those devices, accelerometer sensor is most commonly used for the human activity detection. This activity recognition helps enable successful implementation of smart living spaces applications such as monitoring nurses' activities [1], quality inspection of car production [2], elderly care activities [3], and human health. Researchers have devised many techniques including supervised [4], unsupervised [5], but all of these traditional machine learning techniques use the same settings and domain information to learn those activities. Nevertheless, this require a lot of training and testing data to recognize meaningful activities. These systems again may not work well in different environments, settings and in presence of multiple heterogeneous devices. Inspired by this, we ask a basic question– is there any technique which can cope up with this data, device, domain diversity? To address this cross-cutting diversity, we employ transfer learning technique to build robust and scalable activity recognition model. Researchers have been designing machine learning methods to identify and utilize information collected from one setting (i.e., one home environment to another home environment, different position of the sensors, different human subjects) and transfer to another setting to recognize human activities [6]. This information sharing or transfer based activity recognition helps reduce training time, disparity in model distributions, and helps reuse existing knowledge and learned model to recognize seen and unseen activities in new environment.

In this transfer learning setting, researchers have focused on similar activities in the target environment, particularly encompassing similar data distributions compared to the source environment. In this work, we focus on detecting new activities that may have a different distribution than the source environment. To recognize these activities, activity recognition models generally rely further on the users to gain additional labeled training samples. It is impractical and cumbersome to assume that the users are able to provide a lot of labeled samples as labeling is a time-consuming and cost sensitive task. Therefore, we investigate the feasibility of our proposed *TransAct* model which seeks minimal amount of label information in the target environment to infer human activity through a practical activity recognition model. We also analyze the data interoperability from activity recognition perspectives between two smart devices (smartphone, smart watch), learn knowledge from one device and employ to another. We assume homogeneous feature space, sampling rate and data distribution across two devices.

In this paper, we present a smartphone-based activity recognition system that uses accelerometer signals to accurately identify a range of daily living activities. To solve the data distribution divergence, we posit instance based transfer boost-

978-1-5090-4338-5/17/$31.00 ©2017 IEEE

ing algorithm and classify the new activity instances by using k-means clustering approach. Our main contributions are summarized as follows.

- We study the problem of recognizing activities across different environments (training and testing) in presence of limited target domain labeled data. We depict how our proposed model helps infer new activity that is absent in the source domain.
- We address the challenges of unknown activity recognition potentially fitting to different data distributions compared to source sample data distributions by exploiting an anomaly detection approach in conjunction with clustering.
- We evaluate our model on three public datasets and present the pros and cons of Instance based transfer boost algorithm. We also demonstrate how our proposed *TransAct* model helps overcome some of the deficiencies of Instance based transfer boost technique.

II. Related Work

In this section, we review the related work in two major area: traditional and transfer learning based approach for activity recognition.

Traditional Approach: Activity recognition is a well-investigated topic in the smart home environment setting. Researchers used various types of sensing modalities to sense human activities, for example, ambient sensors, wearable sensors [7][8][9]. Cameras [10], RFID tags [11], Wi-Fi [12], [13] and PIR sensors [14] in smart ambient sensing environment. However, activities can be detected more accurately using wearable sensors because it can capture intricate movements of the human body parts. Accelerometer sensors are mostly used in the wearable sensor setting to keep track of the various human postural movements and activities [15]. In this work, we use smartphone's accelerometer sensor data to infer human activity. Frequency and time-domain features (such as statistical, spectral, etc.) are extracted from sensor signals to train machine learning algorithms for recognizing human activities [16][15]. However, this traditional machine learning algorithm warrants big amount of annotated activity data to establish the hidden correlation between the activity states and sensor data. We address this problem by revitalizing the existing annotated data with few number of new annotated data from the target environment.

Transfer Learning Approach: Researchers are investigating a way to design activity model that can leverage knowledge or information from the previous task into the new task that helps improve the robustness and scalability of the model. Transfer learning mechanisms can help reduce the training time and effort to initiate new activity recognition. Transfer based activity recognition has been applied in various sensor modalities such as video, ambient, and wearable [17][18][6]. Ambient sensing settings require proper sensor placement and users to collaborate collectively to gather activity data. However, in wearable sensing settings, there are less hassle to face with this deployment scheme. Ambient sensors includes a wide range of sensors such as pressure, PIR, motion, door, temperature sensors etc. Instance based learning is the most common in wearable activity recognition. Kurz et al. [21] used the concept of learner and teacher model and built an opportunistic framework that operates in a way such that newly appeared sensors (learners) get trained from the existing ones (teachers). In this framework, teachers helped execute a recognition task by providing activity annotated class to the newly appeared sensors. It incrementally trained and calculated QoS parameters estimating "how much newly arrived information is significant and will contribute in future". Krishan [22] proposed computational framework for detecting gesture and activity by utilizing discriminative classifier that learns spatio-temporal variations in movement patterns for detecting gestures. It employed adaptive discriminative threshold model based filter that helps filters irrelevant movement patterns from continuous sensing signal. Venkatesan [23] has done the cost estimation of older samples and integrated that to boosting based classification algorithm to improve the activity recognition performance. However, these approaches do handle new activities in the target environment and perform poor when a new activity introduces is seen in the target environment. In this work, we used instant based transfer boost algorithm such that it can handle this situation and boost the robustness and scalability of the activity recognition model.

III. Overall TransAct Architecture

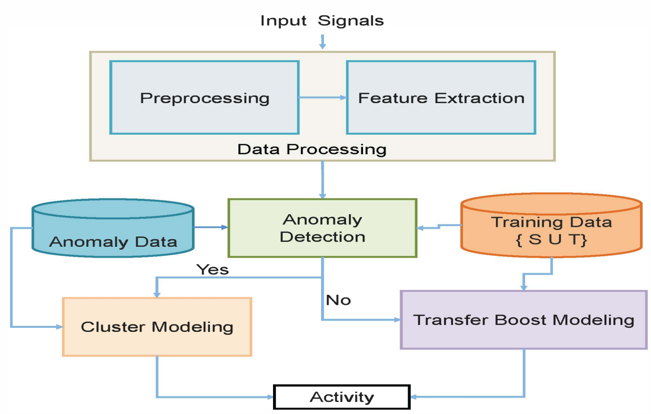


Fig. 1: TransAct Framework

Our TransAct framework consists of following four modules. *i)* Data Processing, *ii)* Anomaly Detection, *iii)* Cluster Modeling, and *iv)* Transfer Boost Modeling. In *data processing* phase, we filter the raw accelerometer signals using a low-pass filter and compute the feature vectors from the filtered signals. In the *anomaly detection* phase, we train transfer boost algorithm using similar and dissimilar activities samples as positive and negative instances from both source and target environments. The negative or positive instances are detected during testing and grouped as anomalies. In the clustering phase, clusters are formed using uncommon activities both from the source and target environments samples data. We assign labels based on the majority voting of data samples classes to each of the cluster. Next, we compute the distance for each anomaly instance to each of the cluster and assign it to the lowest distance cluster. Therefore, transfer boost model helps enhance the classical instance based transfer boost algorithm to recognize existing similar activities in the target environment.

IV. Activity Recognition Methodology

In this section, we describe the details methodology to infer human activity in a new environment. We use instance based transfer learning technique with clustering to help infer human activity. Instance based transfer boosting algorithm performs well where both source and target environment data distributions and activities are similar. Since labeling sensor signals is always cost sensitive task, reusing of training activity samples helps reduce the labeling cost in the target domain. This sharing of knowledge from old environment's activity signals with few labeled samples from the target environment is known as instance based transfer learning. Instance based transfer boosting algorithm [24] helps build an ensemble classifiers to transfer information from source to target environment.

Assume source activity task is $S_i = \{(x_j, y_j)\}_{j=1}^{|S_i|}$ and target environment activity samples is $T = \{(x_i, y_i)\}_{i=1}^{n}$ where each source activity task $S_i \in \{S_1, ..., S_k\}$ has numerous labeled training instances. The goal of transfer boost algorithm is to find the mapping for the target task using the available source instances from $S_1, ..., S_k$. and reweighs source and target environment's activity instances based on the instance transferability metrics. This reweighing factors (α_t, β_t) is defined based on the weighted error [24] of the classifier as shown in Eqn. 1.

$$\epsilon = \sum_{(x_i,y_i)\in T} \frac{w_t(x_i)}{||w_t(T)||_1} |h(x_i) - y_i| \tag{1}$$

Let ϵ_t be the weighted error of hypothesis, h_t on target environment activity dataset T and ϵ_t^i be the weighted error of hypothesis, h_t^i on the source environment activity task S_i at time t. Transferability [24] is defined as the difference between these two factors and mathematically, it is represented as shown in Eqn. 2.

$$\alpha_t^i = \epsilon_t - \epsilon_t^i \tag{2}$$

Transfer boost algorithm greedily sets α_t^i and helps transpose the knowledge from the source task as follows.

- S_i posits positive transfer when $1 \leq exp(\alpha_t^i) \leq e$
- S_i asserts no transfer when $exp(\alpha_t^i) = 1$
- S_i posits negative transfer when $\frac{1}{e} \leq exp(\alpha_t^i) \leq 1$

It trains a model $h_t : X \rightarrow Y$ and reweighs each instance as follows.

- If $(x_i, y_i) \in S_j$, then

$$w_t(x_i) = \frac{w_t(x_i)exp(-\beta_t y_i h_t(x_i) + \alpha_t^j)}{Z_t} \tag{3}$$

- If $(x_i, y_i) \in T$, then

$$w_t(x_i) = \frac{w_t(x_i)exp(-\beta_t y_i h_t(x_i))}{Z_t} \tag{4}$$

where reweighing factor β_t is chosen analytically to minimize the normalization factor β_t and Z_t as shown in Eqn. 5 and Eqn. 6, respectively.

$$\beta_t = \frac{1}{2}\ln\left(\frac{1 + \sum_{j\in D} w_t(x_j)y_j h_t(x_j)}{1 - \sum_{j\in D} w_t(x_j)y_j h_t(x_j)}\right) \tag{5}$$

$$Z_t = \sum_{i=0}^{k} e^{\alpha_t^i} \sum_{j\in S_i} w_t(x_j) e^{-\beta_t y_j h_t(x_j)} \tag{6}$$

We enhance the transfer boost algorithm to recognize unseen activities by introducing the anomaly detection phase. It marks the existing activity samples both in the source and target environment as positive instances and new activity samples as negative instances and train this classifier with both positive and negative instances. This trained model helps infer anomaly when it encounters any negative instances in the target environment. We employ semi-supervised clustering algorithm to assign activity classes to these anomaly instances.

We use k-means clustering algorithm to form clusters from the labeled unseen activity samples. The basic idea behind this approach is to partition the whole set of data into k number of clusters where k is known a-priori. First, we randomly pick up k number of data samples and calculate euclidean distance from each of the data samples to other remaining data samples. If the distance is smaller then the data samples are classified in the same cluster and the process is continued for all the data samples. We compute the mean/centroid of each of the cluster once initial clusters are formed and compare inter-cluster distance with the cluster centroid. We iterate this process until none of the data samples of a cluster possesses minimum distance other than its own cluster. We assign class labels to each cluster based on the majority number of voted class given in the data samples. We calculate the centroid of each cluster, compute the distance between each centroid and the given data samples, and finally assign associated class label to the minimal distance cluster for predicting the human activities.

Algorithm 1 represents our proposed TransAct human activity recognition methodology. $AnomalyDetector$ method takes single instance as an argument and checks whether it belongs to any existing activity class or not. TransAct algorithm posits $ClusterBasedAnnotator$ method for each new activity instance and assigns the appropriate cluster labels to it. It also invokes $TransferBoostAnnotator$ method to infer the proper class labels by sharing knowledge from source to target environment. Finally, annotated activity classes are appended to provide final activity list for a given set of target environment instances. Note that $AnomalyDetector$, $ClusterBasedAnnotator$, and $TransferBoostAnnotator$ methods rely on trained binary transfer boost algorithm, built clusters and trained multi-class transfer boost algorithm, respectively.

Algorithm 1 TransAct Algorithm

Input: Few labeled activity samples in the target environment, D_T
Output: Activity label/class
  //Create Empty Activity List;
  AL = {}
  for $k = 1, ..., |D_T|$ **do**
    if $AnomalyDetector(D_T[k]) = TRUE$ **then**
      $clabel = ClusterBasedAnnotator(D_T[k])$
    else
      $clabel = TransferBoostAnnotator(D_T[k])$
    end if
    $Append(AL, clabel)$
  end for
  return AL

V. Experimental Setup and Evaluation

In this section, we discuss the detailed evaluation of our proposed activity recognition model with 3 different datasets. We evaluate our model while focusing on the following observations: (i) model's overall performance, (ii) comparison of our model with other traditional classifiers, (iii) TransAct's performance over training samples.

A. Data and Setup

We use the public HAR [25], DailyAndSports [26] and MHealth [27] datasets, containing data collected from 30, 8 and 10 users performing 6, 19 and 12 activities, respectively. These datasets contain exercise activities (i.e. walking on a treadmill, cycling on a bike etc.) and basic daily activities (standing, walking etc.).

We consider Java based platform to implement our model. We segment the accelerometer data using sliding window based protocol and create frames with 128 sample data points with 50% overlap from the raw accelerometer signals. We keep the frame length consistent across all the datasets. We filter raw accelerometer sensor signals to remove noise using low-pass filter and provide smooth signals which help improve activity recognition accuracy. To determine the band for the filter, we applied FFT on the data and found that most of the high-energy frequency components lie in between 0-20 Hz. Therefore, we applied a low-pass filter with a maximum frequency of 20 Hz and used filtered data to calculate corresponding features.

We extracted and exploited both the time domain and frequency domain features. Time domain features like mean, standard deviation etc., and frequency domain features like energy, entropy etc., of the signals, are calculated using Fast Fourier Transform (FFT) on each frame. On top of that, we exploited frequency normalization by applying Hamming window. Corresponding features of our activity recognition model are summarized in Table I.

We evaluated and compared the performance of our activity recognition model based on the following metrics. *i)* Precision $= (\frac{TP}{TP+FP})$, *ii)* Recall $R = (\frac{TP}{TP+FN})$, *iii)* F-1 Score$= \frac{2\times P\times R}{P+R}$ and, *iv)* Accuracy $= \frac{TP+TN}{TP+TN+FP+FN}$,

TABLE I: Activity recognition features for classification

Domain	Features
Time Domain	Mean($\bar{x}, \bar{y}, \bar{z}$), Standard Deviation ($\sigma_x, \sigma_y, \sigma_z$) Variance ($var(x), var(y), var(z)$) Corr. Coefficient($\frac{Cov(x,y)}{\sigma_x\sigma_y}, \frac{Cov(y,z)}{\sigma_y\sigma_z}, \frac{Cov(x,z)}{\sigma_x\sigma_z}$) Magnitude($\sqrt{(x^2+y^2+z^2)}$)
Frequency Domain	Energy($\frac{\sum_{i=1}^{n} f_{x_i}^2}{n}, \frac{\sum_{i=1}^{n} f_{y_i}^2}{n}, \frac{\sum_{i=1}^{n} f_{z_i}^2}{n}$) Entropy($-\sum_{i=1}^{n} p_i \ln p_i$), $p_i = \frac{f_i}{\sum_{i=1}^{n} f_i}$

where TP, FP, TN, and FN are the number of instances of true positive, false positive, true negative and false negative, respectively.

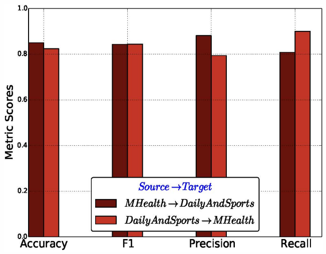
B. TransAct Model's Performance

We evaluate the performance of our model in two scenarios, with (i) similar activities in both environments, and (ii) new activities in the target environment.

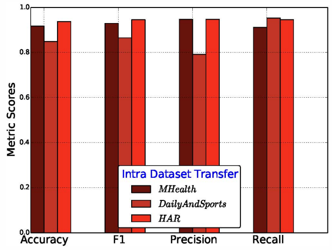
(i) Similar activities in both environment: In this setting, we evaluate the performance of our activity recognition model both on inter- and intra-dataset. Figure 2 depicts overall performance of our TransAct model. In the intra-dataset settings, we split the number of subjects randomly to create two environments and use one as a source and another one as a target. Figure 2b depicts the performance results of our intra-environment activity recognition model. In this setting, our model achieves fairly good accuracy because data distributions depend only on the subject's activity performance. We notice that our model achieves an accuracy of 93% and 82% for HAR dataset and DailyAndSports dataset, respectively 2b. It shows lower accuracy for DailyAndSports dataset because there exists larger variations in speed and amplitude among inter-subject activity sets.

In the inter-dataset setting, we consider common activities from both MHealth and DailyAndSports with sensor position being on chest and torso, respectively. We use one dataset as source environment and other as target environment. Figure 2a represents inter-dataset performance of our TransAct model. Our model achieves 85% and 82% accuracy while we employ DailyAndSports and MHealth as target environment, respectively. Note that TransAct model's performance has been degraded in this case compared to intra-dataset scenario because of larger variation in data distributions. The differences in bias and gain of the sensors and the users' agility in performing different activities including their individual age from both the source and target environments greatly influence the performance of our proposed activity model.

(ii) New activities in the target environment: In this setting, we evaluate the performance of our TransAct model for new activities in the target environment. Figure 3 shows overall performance of our model. We evaluate our model in two scenarios: (i) inter-dataset activity transfer, and (ii) intra-dataset activity transfer. In the first scenario, we transfer knowledge from MHealth to DailyAndSports and vice versa. In the target environment (DailyAndSport dataset), we consider playing



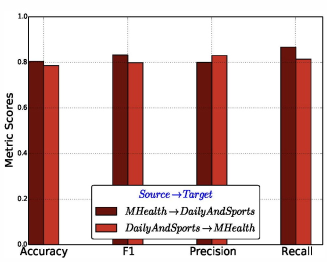
(a) Activity recognition performance for MHealth and DailyAndSports datasets.



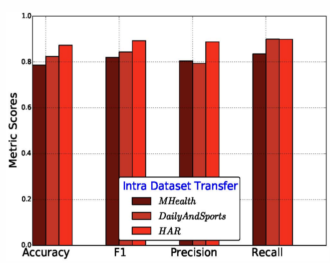
(b) Activity recognition performance for intra dataset.

Fig. 2: TransAct Model Performance for Existing Activities

basketball as a new activity as it is not present in the source environment (MHealth dataset). We incrementally select and classify one or more new activities from the target domain in conjunction with existing common activities as available in source environment. Figure 3a depicts the overall performance of our TransAct model in this case. It shows F1 score (0.83), precision (0.80) and recall (0.86) values. Note that higher precision and recall values help confirm that our model has not been overfitted in the context of new and unseen activity recognition. Figure 3b depicts the efficacy of intra-dataset activity knowledge transfer for recognizing new activities in the target environment with 87% accuracy for HAR dataset. We note that our proposed TransAct model performs better in case of intra-dataset than inter-dataset activity knowledge transfer. The less diversified data distributions in this case compared to inter-dataset and the augmentation of semi-supervised clustering algorithm to assign new activity instance in the appropriate cluster help improve the performance.



(a) Activity recognition performance for MHealth and DailyAndSports datasets.



(b) Activity recognition performance for intra dataset.

Fig. 3: TransAct Model Performance for New Activities

C. *TransAct Model vs Training Samples*

To better understand the impact of new activities in the target environment, we further extend our experimentations with respect to the number of training samples. Figure 4 shows the precision and recall of our model while recognizing new activities. We observe that recall drifts substantially while the number of samples are small but it remains consistent in presence of the increasing number of training samples. We also note that the higher recall indicates the effectiveness of our model for recognizing new activity samples while reducing the false negative rate.

TABLE II: Comparison of Classifiers

Dataset	DT	RF	TB	TransAct
HAR	76.73	71.96	75.65	86.49
MHealth	48.02	62.25	66.48	77.43
DailyAndSports	66.67	70.38	72.86	80.73
Avg. Accuracy	**63.81**	**68.20**	**71.66**	**81.55**

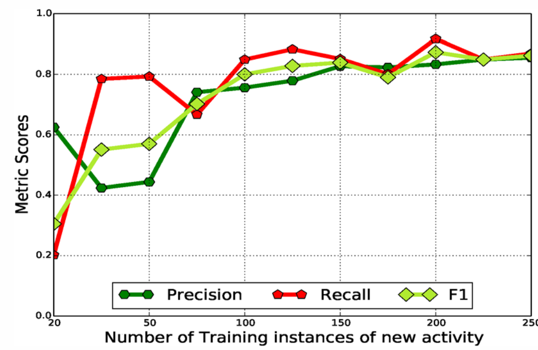


Fig. 4: Number of training instance of new activity

D. *Comparison of different classifiers*

We compare the performance of TransAct model with existing methodologies such as including Random Forest (RF), Decision Tree (DT) and Transfer Boost (TB). We use Weka machine learning algorithms toolkits for RF and DT implementations and we create our own Java implementation for TB. We perform the experiments for intra-dataset environments with varied new activities where activities are chosen randomly in each run. Table II shows the detail results. Note that TransAct model achieves an average accuracy $\approx$ 81% whereas TB achieves $\approx$ 72% accuracy. TransAct achieves higher accuracy compared to the other classifiers because it handles new unseen activities instances as anomalies and then assign them into the appropriate clusters which help boost the classification accuracy.

VI. Conclusion

In this work, we proposed a novel activity recognition model, TransAct which helps recognize activities in the new environment while accessing and transferring knowledge from differing source data and activity distributions. Our model is able to recognize activities with limited training instances in the target environment. It utilizes source environments labeled data to learn the activity model for the new environment that may have few labeled samples and new activities. We address this problem by deploying transfer boost algorithm with clustering mechanism to recognize activities in heterogeneous environments, activities, devices and data samples settings. This model is robust enough to spot complex activities also. In future, we plan to recognize sub-activities with this model and add sequence recognizer to infer complex activities.

VII. ACKNOWLEDGMENT

This work is partially supported by the ONR under grant N00014-15-1-2229.

REFERENCES

[1] Dominick Sanchez, Monica Tentori, and Jesús Favela. Activity recognition for the smart hospital. *Intelligent Systems, IEEE*, 23(2):50–57, 2008.

[2] Georg Ogris, Thomas Stiefmeier, Paul Lukowicz, and Gerhard Tröster. Using a complex multi-modal on-body sensor system for activity spotting. In *Wearable Computers, 2008. ISWC 2008. 12th IEEE International Symposium on*, pages 55–62. IEEE, 2008.

[3] TLM Van Kasteren, Gwenn Englebienne, and Ben JA Kröse. An activity monitoring system for elderly care using generative and discriminative models. *Personal and ubiquitous computing*, 14(6):489–498, 2010.

[4] Sotiris B Kotsiantis. Supervised machine learning: A review of classification techniques, 2007.

[5] Trevor Hastie, Robert Tibshirani, and Jerome Friedman. *Unsupervised learning*. Springer, 2009.

[6] Diane Cook, Kyle D Feuz, and Narayanan C Krishnan. Transfer learning for activity recognition: A survey. *Knowledge and information systems*, 36(3):537–556, 2013.

[7] Daniel Olguın Olguın and Alex Sandy Pentland. Human activity recognition: Accuracy across common locations for wearable sensors. Citeseer.

[8] Koji Yatani and Khai N Truong. Bodyscope: a wearable acoustic sensor for activity recognition. In *Proceedings of the 2012 ACM Conference on Ubiquitous Computing*, pages 341–350. ACM, 2012.

[9] Jungsoo Kim, Jiasheng He, Kent Lyons, and Thad Starner. The gesture watch: A wireless contact-free gesture based wrist interface. In *Wearable Computers, 2007 11th IEEE International Symposium on*, pages 15–22. IEEE, 2007.

[10] JK Aggarwal and Lu Xia. Human activity recognition from 3d data: A review. *Pattern Recognition Letters*, 48:70–80, 2014.

[11] Dany Fortin-Simard, J Bilodeau, Kevin Bouchard, Sebastien Gaboury, Bruno Bouchard, and Abdenour Bouzouane. Exploiting passive rfid technology for activity recognition in smart homes. 2015.

[12] Lin Liao. *Location-based activity recognition*. PhD thesis, University of Washington, 2006.

[13] Tong Zhang, Jue Wang, Ping Liu, and Jing Hou. Fall detection by embedding an accelerometer in cellphone and using kfd algorithm. *International Journal of Computer Science and Network Security*, 6(10):277–284, 2006.

[14] Geetika Singla, Diane J Cook, and Maureen Schmitter-Edgecombe. Recognizing independent and joint activities among multiple residents in smart environments. *Journal of ambient intelligence and humanized computing*, 1(1):57–63, 2010.

[15] Jennifer R Kwapisz, Gary M Weiss, and Samuel A Moore. Activity recognition using cell phone accelerometers. *ACM SigKDD Explorations Newsletter*, 12(2):74–82, 2011.

[16] U. Maurer, A. Smailagic, D.P. Siewiorek, and M. Deisher. Activity recognition and monitoring using multiple sensors on different body positions. In *Wearable and Implantable Body Sensor Networks, 2006. BSN 2006. International Workshop on*, pages 4 pp.–116, April 2006.

[17] Lixin Duan, Dong Xu, IW-H Tsang, and Jiebo Luo. Visual event recognition in videos by learning from web data. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 34(9):1667–1680, 2012.

[18] Ulf Blanke and Bernt Schiele. Remember and transfer what you have learned-recognizing composite activities based on activity spotting. In *Wearable Computers (ISWC), 2010 International Symposium on*, pages 1–8. IEEE, 2010.

[19] TLM Van Kasteren, Gwenn Englebienne, and Ben JA Kröse. Transferring knowledge of activity recognition across sensor networks. In *Pervasive computing*, pages 283–300. Springer, 2010.

[20] Vincent Wenchen Zheng, Sinno Jialin Pan, Qiang Yang, and Jeffrey Junfeng Pan. Transferring multi-device localization models using latent multi-task learning. 2008.

[21] Marc Kurz, Gerold Hölzl, Alois Ferscha, Alberto Calatroni, Daniel Roggen, and Gerhard Tröster. Real-time transfer and evaluation of activity recognition capabilities in an opportunistic system. *machine learning*, 1(7):8, 2011.

[22] Narayanan Chatapuram Krishnan. *A computational framework for wearable accelerometer-based*. PhD thesis, Arizona State University, 2010.

[23] Ashok Venkatesan, Narayanan C Krishnan, and Sethuraman Panchanathan. Cost-sensitive boosting for concept drift. 2010.

[24] Wenyuan Dai, Qiang Yang, Gui-Rong Xue, and Yong Yu. Boosting for transfer learning. In *Proceedings of the 24th international conference on Machine learning*, pages 193–200. ACM, 2007.

[25] Jorge-L Reyes-Ortiz, Luca Oneto, Albert Samà, Xavier Parra, and Davide Anguita. Transition-aware human activity recognition using smartphones. *Neurocomputing*, 171:754–767, 2016.

[26] Billur Barshan and Murat Cihan Yüksek. Recognizing daily and sports activities in two open source machine learning environments using body-worn sensor units. *The Computer Journal*, 57(11):1649–1667, 2014.

[27] Oresti Banos, Rafael Garcia, Juan A Holgado-Terriza, Miguel Damas, Hector Pomares, Ignacio Rojas, Alejandro Saez, and Claudia Villalonga. mhealthdroid: a novel framework for agile development of mobile health applications. In *International Workshop on Ambient Assisted Living*, pages 91–98. Springer, 2014.