DAPPER: Performance Estimation of Domain Adaptation in Mobile Sensing

TAESIK GONG, School of Computing, KAIST, Republic of Korea
YEWON KIM, School of Electrical Engineering, KAIST, Republic of Korea
ADIBA ORZIKULOVA, School of Electrical Engineering, KAIST, Republic of Korea
YUNXIN LIU, Institute for AI Industry Research (AIR), Tsinghua University, China
SUNG JU HWANG, Graduate School of AI, KAIST and AITRICS, Republic of Korea
JINWOO SHIN, Graduate School of AI, KAIST, Republic of Korea
SUNG-JU LEE, School of Electrical Engineering, KAIST, Republic of Korea

Many applications that utilize sensors in mobile devices and apply machine learning to provide novel services have emerged. However, various factors such as different users, devices, environments, and hyperparameters, affect the performance for such applications, thus making the domain shift (i.e., distribution shift of a target user from the training source dataset) an important problem. Although recent domain adaptation techniques attempt to solve this problem, the complex interplay between the diverse factors often limits their effectiveness. We argue that accurately estimating the performance in untrained domains could significantly reduce performance uncertainty. We present DAPPER (Domain AdaPtation Performance EstimatoR) that estimates the adaptation performance in a target domain with only unlabeled target data. Our intuition is that the outputs of a model on the target data provide clues for the model’s actual performance in the target domain. DAPPER does not require expensive labeling costs nor involve additional training after deployment. Our evaluation with four real-world sensing datasets compared against four baselines shows that DAPPER outperforms the baselines by on average 17% in estimation accuracy. Moreover, our on-device experiment shows that DAPPER achieves up to 216× less computation overhead compared with the baselines.

CCS Concepts: • Human-centered computing → Ubiquitous and mobile computing systems and tools.

Additional Key Words and Phrases: Mobile sensing; Deep learning; Domain adaptation; Performance estimation

ACM Reference Format:
Taesik Gong, Yewon Kim, Adiba Orzikulova, Yunxin Liu, Sung Ju Hwang, Jinwoo Shin, and Sung-Ju Lee. 2021. DAPPER: Performance Estimation of Domain Adaptation in Mobile Sensing. J. ACM 0, 0, Article 0 (2021), 26 pages.

1 INTRODUCTION

Mobile sensing utilizes the sensors from mobile devices (e.g., smartphones and wearables) to infer user contexts and provide appropriate services accordingly. Integrated with the power of deep learning, which enables understanding of multi-dimensional sensory data, mobile sensing has broad applications ranging from human...
activity recognition [48, 50, 56] to driving context recognition [38, 72], authentication [4, 36, 80], emotion recognition [37, 40], and healthcare [76–78]. While a body of research in this area has demonstrated its potential, existing methods have been limited in real-world deployments due to the domain shift issue, i.e., distribution shift of target data with respect to training (or source) data. [15, 58, 63]. Specifically, users have different physical conditions and behaviors, and their mobile devices have various specifications, making each user’s sensing distribution different from others. Therefore, a pre-trained model typically suffers from poor generalization to an unseen user and device. A popular approach in addressing this problem is domain adaptation that utilizes a few labeled/unlabeled samples [3, 10, 15, 24, 69, 81] to adapt to the target condition.

Domain adaptation for mobile sensing is particularly challenging as countless combinations between users and devices, the quality and quantity of the target samples, numerous hyperparameters, and even software/hardware are known to affect the model’s performance [39, 44]. With various factors affecting the performance, it is difficult to predict how the model will perform after adaptation. A common evaluation method in domain adaptation is to set a fixed number of training epochs (e.g., 100) and report the last epoch’s performance [2, 7, 10, 11, 20, 28, 32, 35, 55, 59, 67, 70, 81]. However, the model performance significantly varies with respect to training epochs, and selecting the last epoch’s model is often far from being optimal, falling into the following problems: (i) the adapted performance is often worse than the performance without adaptation, (ii) the accuracy of the model saturates too early, and (iii) the model accuracy largely fluctuates during training, with the best model found in the middle of training. Therefore, merely choosing the last epoch’s model often leads to sub-optimal (or even worst) performance and requires unnecessary training overhead. To avoid such undesirable situations, performance validation is critical regardless of how effective an adaptation algorithm is. To validate the model’s performance, many studies have collected labeled test data from a target domain and reported the best accuracy [6, 9, 15, 23, 34, 61, 62, 68, 69, 71]. However, it is extremely costly and unrealistic to require every user to collect data and manually label them.

We propose DAPPER (Domain AdaPtation Performance EstimatoR), a performance estimation framework for domain adaptation in mobile sensing (Figure 1). DAPPER leverages only unlabeled target data for estimating performance. As unlabeled time-series sensory data could be naturally collected in mobile sensing applications, it does not require additional user labeling efforts. Our key intuition is that the model outputs on unlabeled target data could be an effective proxy for the actual model performance on the target domain. Specifically, we propose three novel proxies that are statistically correlated with the model performance. Here, we model the relationship between the proxies and the adapted performance via neural networks. We train DAPPER

Fig. 1. DAPPER estimates the adaptation performance utilizing only the unlabeled data from the target user.
with simulated adaptation data generated from the source data. As DAPPER requires training only once before deployment, it does not incur extra training overhead on target devices, which is beneficial in resource-constrained mobile devices. To the best of our knowledge, DAPPER is the first proposal of performance estimation with unlabeled data to combat the uncertainty of the adapted performance in mobile sensing.

We evaluate our proposed method with four real-world datasets: Heterogeneity Human Activity Recognition (HHAR) [58], Wearable Stress and Affect Detection (WESAD) [53], Individual-Condition Human Activity Recognition (ICCHAR) [15], and Individual-Condition Speech Recognition (ICSR) [15]. We demonstrate the effectiveness of our method compared with four baselines, including the state-of-the-art learning-based performance estimation algorithm for domain adaptation [5]. Our empirical result shows that DAPPER is the most accurate performance estimator, outperforming the baselines by 17% on average with respect to estimation accuracy. We further evaluate the computation efficiency of our method by implementing DAPPER and the baselines on mobile devices with the Mobile Neural Network (MNN) framework [22]. The result shows that DAPPER requires 16−258× less computation overhead than the existing training-based algorithm, 2.5−3.2× less overhead than training until a fixed epoch, and only 0.4 ms additional computation latency than the direct calculation of the performance with a labeled test data.

We summarize our contributions as follows:

- We highlight the importance of performance validation in domain adaptation for mobile sensing by uncovering the performance dynamics and uncertainty under domain shifts.
- We present DAPPER, a performance estimation framework with unlabeled target data without additional training, by utilizing model outputs as a proxy for the performance. We believe DAPPER is the first proposal of performance estimation with unlabeled data to combat the uncertainty of the adapted performance in mobile sensing.
- We conduct extensive experiments with four real-world datasets against four baselines. Our evaluation indicates that DAPPER outperforms the baselines in terms of estimation accuracy. Moreover, our on-device computation overhead analysis shows that DAPPER requires significantly less computation overhead than the training-based baseline and yields only marginal overhead than the direct calculation of the performance with labeled test data.

2 BACKGROUND AND MOTIVATION

2.1 Performance Dynamics in Mobile Sensing

In mobile sensing, users have different behaviors and physical characteristics. For instance, an elderly’s “jogging” might be confused with a young’s “walking.” Moreover, their mobile devices also have diverse specifications, such as different shapes, weights, sensing sampling rates, etc. In addition, the placement of mobile devices varies according to the type of device (smartphone vs. smartwatch) and user’s preference (hand vs. pocket). These differences collectively create a unique sensing condition for each individual [15, 58, 63], which makes domain shift (i.e., distribution shift of the target data with respect to the source data) an inevitable problem in mobile sensing. Since it is unrealistic to pre-train models for all possible combinations of conditions in advance, domain adaptation (DA) algorithms have been proposed. Given a model trained on one or more source domains, a domain adaptation algorithm utilizes a few labeled and/or unlabeled target data to adapt to the target domain [3, 10, 15, 24, 69, 81]. These studies have demonstrated that domain adaptation could be a promising approach to overcome the domain shift problem in mobile sensing.

While previous research has focused on the algorithmic aspect of domain adaptation, we argue that the performance dynamics in the adaptation stage must be addressed. In addition to the user and device heterogeneity
in mobile sensing, numerous other factors affect the adapted performance. For instance, the quality and quantity of the data from the target user are usually not guaranteed (e.g., mislabeling, skewed data distribution, etc.). The model design such as model architecture, set of hyperparameters, or training algorithms lies in a huge space and is known to be extremely difficult to optimize [39]. When the model is deployed, both software (OSes, library versions, etc.) and hardware (GPUs, etc.) specifications on which adaptation is applied also impact the performance [44].

To see how various factors affect adaptation performance, we conducted a preliminary empirical study using the Heterogeneity Human Activity Recognition (HHAR) dataset [58] and an unsupervised domain adaptation (UDA) algorithm [32] (details in §4). We considered a common multi-source DA scenario: for each target domain, we pre-trained a base model with the remaining domains, and the base model was adapted to the target domain. We varied diverse factors that impact the adaptation performance: the target domain, the number of target samples, the distribution of samples with respect to classes, the learning rate, the optimizer, and the algorithm-specific hyperparameter (balancing factor); we controlled all other factors.

Figure 2 visualizes the accuracy on the target test dataset as the adaptation proceeded for 100 training epochs. It shows that the adaptation accuracy has diverse patterns according to a variety of factors. As multiple factors interplay and some are beyond the developer’s control, it is difficult to predict the adapted performance.

2.2 Limitations of Previous Approaches

We found that common approaches in performance validation for domain adaptation have critical limitations. Many studies used a fixed number of training epochs and report the accuracy at the last epoch [2, 7, 10, 11, 20, 28, 32, 35, 55, 59, 67, 70, 81]. However, simply selecting the model at the last epoch suffers from several critical issues, as we illustrate in Figure 3. First, in some cases, adaptation results in undesirable performance degradation due to numerous factors, as discussed in §2.1. Second, if the model’s accuracy has rapidly saturated in the first few epochs, training for more epochs will bring in unnecessary computational overhead. Third, the model’s accuracy can fluctuate and reach its maximum in the middle of training. Thus, selecting the last epoch’s model without a proper performance validation might lead to selecting a sub-optimal model.
3.1 Overview

We aim to estimate the performance with unlabeled data from the target user. In mobile sensing, unlabeled time-series sensory data can typically be collected from a target user without the user’s manual effort [1, 60]. Our idea is to utilize such unlabeled data to estimate the performance of the adapted model. Figure 4 shows the workflow of our performance estimation framework. We follow a common domain adaptation setting, where a pre-trained model with source data is deployed to a user as an initial model and is adapted to the target user with
some training data from the target domain [15, 32]. Our goal here is to estimate the change in performance of the adapted model as close as possible to the change in performance calculated from the labeled data, utilizing only unlabeled data from the target domain. We estimate the performance via a domain adaptation performance estimator, DAPPER, which we detail in §3.3.

Formally, let $D_S = \{x^{(i)}_S, y^{(i)}_S\}_{i=1}^{N_S}$ be the source data collected from one or more domains and $D_T = \{x^{(i)}_T, y^{(i)}_T\}_{i=1}^{N_T}$ be the target data to adapt to, where $x^{(i)}$ and $y^{(i)}$ denote data instances and their corresponding labels regardless of their subscripts. We consider a realistic scenario where $D_S$ does not include $D_T$, i.e., $D_S \cap D_T = \emptyset$. Let $D_T^{tr}$ be training data for adaptation and $D_T^{va}$ be unlabeled validation data, where $D_T^{tr}, D_T^{va} \subset D_T$, and $D_T^{tr} \cap D_T^{va} = \emptyset$. We want to estimate the adapted model’s performance with unlabeled target validation data, $D_T^{va}$. We are interested in the target accuracy,$^1$ which is the most representative metric of performance. We focus on estimating the change in the target accuracy as adaptation proceeds. We use the terms "performance" and "accuracy" interchangeably throughout the paper. Specifically, the target accuracy at epoch $e \in E = \{0, 1, 2, ..., T\}$ is defined as

$$a^{(e)} = \frac{\sum_{(x_T, y_T) \in D_T^{va}} \mathbb{1}_{[\hat{y}^{(e)}_T = y_T]} }{|D_T^{va}|},$$

(1)

where $\hat{y}^{(e)}_T$ is a predicted label with an adapted model at epoch $e$ ($f^{(e)}_\theta$), and $\mathbb{1}_{[\hat{y}^{(e)}_T = y_T]}$ is one if $\hat{y}^{(e)}_T = y_T$ and zero otherwise. Accordingly, the change in the target accuracy at epoch $e$ is defined as follows:

$$\Delta a^{(e)} = a^{(e)} - a^{(0)},$$

(2)

which represents how accuracy changed after adaptation compared against without adaptation. Our objective is to minimize the difference between the change in accuracy and the estimated change in accuracy computed from the unlabeled target validation data ($D_T^{va}$) during the training epochs, which is defined as follows:

$$\text{minimize } \sum_{e=1}^{T} \left| \Delta a^{(e)} - \hat{a}^{(e)} \right|,$$

(3)

where $\hat{a}^{(e)}$ is the estimated accuracy of $f^{(e)}_\theta$ through $D_T^{va}$.

As we described in §2.2, prior studies usually (i) train until a predefined number of epochs without validation, which could lead to performance degradation or unnecessary training overhead, or (ii) require labeled target validation data to compute accuracy directly, which is costly and impractical. Note that it is extremely challenging, if not impossible, to compute the exact performance for a target domain without labeled data. We tackle this

$^1$We have also tried other metrics, such as the F1 score, and observed similar findings throughout the experiments.

J. ACM, Vol. 0, No. 0, Article 0. Publication date: 2021.
problem by leveraging model outputs as a proxy of the model performance. Our key finding is that there is a correlation between the model outputs on the target data and the model’s actual performance on the target domain. Note that a desirable performance estimator should involve minimal user effort. By utilizing only unlabeled data, DAPPER does not require any labeling effort from the user. Moreover, DAPPER requires training only once before the deployment (from the developer side), thus it incurs negligible computation overhead from the user side.

3.2 Model Outputs as a Proxy of Model Performance

We first explore the correlation between the model outputs on target validation data and the model’s performance. Our motivation is that while a single output might have limited information on the model, a collection of outputs would reveal hints for the model performance. We introduce three proxies for the performance of the adapted model, calculated from the model outputs on the target data: mean confidence (Conf), prediction diversity (Div), and pseudo-label distribution (Dist).

3.2.1 Mean Confidence. Studies have demonstrated that increasing the confidence of the model prediction leads to performance improvements [16, 64, 65]. Inspired by this, we inspect the correlation between the mean confidence (Conf) of the predictions on target validation data and the performance of the model on the target domain. Our intuition is that the model’s overall confidence in the target data can be an indicator of the model’s performance on the target domain.

In a multi-class classification problem, while the final classification is discrete, the softmax output of a model can be interpreted as the confidence of the model for each class. Specifically, given an unlabeled target sample \( x_T^{(i)} \in D_T^{va} \) and an adapted model \( f_\theta \), we can get the softmax output \( q^{(i)}_T \) for \( x_T^{(i)} \), i.e.,

\[
q^{(i)}_T = \text{Softmax}(f_\theta(x_T^{(i)})) = [q_1^{(i)}, q_2^{(i)}, \ldots, q_K^{(i)}],
\]

where \( q_k^{(i)} = P(y_T^{(i)} = k|x_T^{(i)}) \), \( \sum_{k=1}^{K} q_k^{(i)} = 1 \), \( K \) is the number of classes.

Now we consider the entropy [54] of the predicted softmax output. Entropy is used as a metric for how confident the model’s prediction is by measuring the uncertainty of the output categorical distribution, i.e., the lower the entropy, the higher the confidence [29]. Entropy minimization (or confidence maximization) has been a successful learning objective in semi-supervised learning and unsupervised domain adaptation [16, 64, 65], where decreasing the uncertainty (entropy) of the model’s prediction results in performance improvements. Our motivation behind repurposing entropy as a proxy of performance is that not only can it be a learning objective, but it can also be an indicator of the adapted model’s performance by considering the overall confidence of the model on the target data. Specifically, we calculate the entropy of the predicted softmax output as follows:

\[
\text{Entropy}(q^{(i)}) = -\sum_{k=1}^{K} q_k^{(i)} \cdot \log(q_k^{(i)}).
\]

Accordingly, we define the mean confidence (Conf) calculated from the mean entropy on all data in \( D_T^{va} \), i.e.,

\[
\text{Conf}(D_T^{va}) = -\frac{1}{|D_T^{va}|} \sum_{i=1}^{|D_T^{va}|} \text{Entropy}(q^{(i)}).
\]

Therefore, Conf is a statistical estimation for the overall certainty of the model on the target domain.

We conduct an empirical study to investigate the relationship between Conf and accuracy. We ran training with supervised domain adaptation (SDA) and unsupervised domain adaptation (UDA) algorithms across four sensory
datasets (HHAR, WESAD, ICHAR and ICSR) with 10k data points for each dataset (details in §4). Figure 5 shows the correlation between Conf and accuracy across four datasets. The error bars represent standard deviations.

As shown, a positive correlation exists between accuracy and Conf; the higher the Conf, the higher the accuracy. However, Conf is not strong enough to be an accurate proxy for measuring accuracy. Most importantly, a very high Conf is sometimes negatively correlated to accuracy, which is shown as an accuracy drop (Figure 5b, 5c, and 5d). This happens when a model is adapted poorly yet generates confident scores for erroneous classes [17]. For instance, when a model classifies all inputs as one specific class with high confidence (i.e., trivial solution), the Conf is high while the accuracy is low. Besides, Conf shows high variance depending on datasets.

3.2.2 Prediction Diversity. In the previous experiment, we found that while Conf positively correlates with accuracy, a high Conf is often related to poor accuracy due to overfitting. We discovered that the worse the model performance after adaptation, the more biased the predictions towards certain classes. To understand this
We then define prediction diversity (Div) as:

\[ \text{Div}(\mathcal{D}) = \text{Entropy}(q_{\mathcal{D}}^{\text{va}}) \]  

(8)

Therefore, Div represents how diversified the predicted results over target validation data are without being biased towards certain classes.

Figure 7 visualizes the relationship between the prediction diversity and the accuracy with the same datasets as Figure 5. Similar to Conf, Div has a positive correlation with accuracy. This implies that measuring the prediction diversity of the adapted model could be a proxy of model accuracy as well. While Div seems to mitigate the problem of overfitting in Conf, Div by itself is not a perfect estimator for accuracy; in some cases, it has no correlation, even shows a negative correlation (e.g., Figure 7b), or has high standard deviations depending on datasets.

3.2.3 Pseudo-label Distribution. Note that Conf and Div do not consider class-specific information; they are statistical metrics calculated over all classes. However, class-specific information often reveals the inherent characteristics of datasets related to performance [18]. For instance, distinguishing between “sitting” and “lying” via motion sensors might be more difficult than distinguishing between “sitting” and “jumping,” due to similar features. Accordingly, a model with good performance would better classify those confusing classes compared to a model with bad performance.

In order to take advantage of the class-specific information for performance estimation, we investigate pseudo-label distribution (Dist). Dist represents the proportion of predicted labels on the target validation data, which is defined as:

\[ \text{Dist}(\mathcal{D}) = [p_1, p_2, \ldots, p_K], \quad \text{where} \quad p_k = \frac{1}{|\mathcal{D}|} \sum_{x \in \mathcal{D}} \mathbb{1}_{[f_0(x) = k]} \quad \text{and} \quad \sum_{k=1}^{K} p_k = 1. \]  

(9)
Gong et al.

(a) HHAR dataset. (b) WESAD dataset. (c) ICHAR dataset. (d) ICSR dataset.

Fig. 8. Comparison between the predicted accuracy from pseudo-label distribution and the true accuracy across four datasets.

While Conf and Div have no class information, Dist contains the information about the predicted classes for validation data.

To investigate whether Dist could be a proxy for performance, we conducted an experiment where we modeled a linear relationship between the true accuracy and the estimated accuracy via a simple 1D linear regression. Figure 8 shows a positive, albeit not strong, correlation between the predicted accuracy and the ground-truth accuracy. This implies we can model the relation from Dist to the true accuracy by capturing dataset-specific characteristics that appear in the pseudo-label distribution (e.g., relative proportions among classes).

3.2.4 Takeaways. We summarize the key takeaways throughout this preliminary experiment as follows:

- Conf, Div, and Dist show a positive correlation with adapted accuracy and could be proxies for measuring adapted accuracy.
- Neither Conf, Div, nor Dist has a strong correlation to be an accurate estimator by itself; high variances and exceptional cases are occasionally observed.
- The correlation depends on datasets, showing different patterns across the four datasets.

Motivated by the above takeaways, we train a performance estimator that benefits from the proxies’ positive correlations with accuracy while mitigating their limitations, which we detail in the following section.

3.3 DAPPER

We train a domain adaptation performance estimator, DAPPER, that gets the outputs of an adapted model on $\mathcal{D}_{T}$ and predicts the change in accuracy. Based on the findings from the previous experiment (§3.2), our motivations to train a performance estimator are three-fold: (i) All three proxies from different intuitions show positive correlations with adapted accuracy, and thus utilizing them together could be an accurate proxy for performance, (ii) machine learning can capture the underlying optimal relation from the proxies to the true accuracy with sufficient training data, and (iii) dataset-dependent characteristics could be learned by training dataset-dependent estimators.

Practical concerns for training such an estimator would be the cost of data collection and computation overhead. DAPPER resolves the concerns by (i) generating lots of training data using already collected source data and (ii) decoupling the training process from the user side. DAPPER generates training data with source data only via simulation. The entire training process of DAPPER is conducted on the developer side. Therefore, once deployed to users, only inference is required for estimation.

3.3.1 Training Data Generation. We generate training data to meet the following objectives. First, we create training data only from source data. Collecting target data is not required to train DAPPER, which is beneficial in terms of cost and effort. Second, we want to train with as diverse data as possible to make DAPPER robust to various scenarios. Figure 9 is an illustration of the training process. The training starts from training data generation with the source data (Figure 9a). Note that we do not have access to the target data that is ideal for
training the estimator with. We instead simulate adaptation with the source data to generate the training data for DAPPER. We assume the developer collected or obtained the source datasets from multiple domains, and we randomly split the source data into non-overlapping virtual-source domains and virtual-target domains. With the virtual-source and virtual-target, we generate the training data by simulating adaptation; the model is pre-trained with the virtual-source data, and the adaptation algorithm is applied to the pre-trained model to adapt to the virtual-target. We randomly sample the virtual-target training and validation data to simulate diverse adaptation scenarios. While adapting to the virtual-target data, features are calculated for every epoch from the unlabeled virtual-target validation data. We also log accuracy as the ground truth. This process is repeated $M$ times to generate enough training data. We evaluate the impact of $M$ in §5.5.

3.3.2 Training DAPPER. We train DAPPER after the data is generated from the source data (Figure 9b). We adopt six features as the inputs for DAPPER and an LSTM model as the architecture, which we detail as follows.

**Features:** As shown in the preliminary experiment, we regard Conf, Div, and Dist as effective proxies for estimating adapted accuracy. We use Conf, Div, and Dist calculated from the virtual target validation data as input features. In addition, we use the difference from the previous values as additional input features, i.e.,

$$\text{Diff}_e = \text{Conf}_e - \text{Conf}_{e-1}, \quad \text{Diff}_{\text{Div}}e = \text{Div}_e - \text{Div}_{e-1}, \quad \text{and} \quad \text{Diff}_{\text{Dist}}e = \text{Dist}_e - \text{Dist}_{e-1}. \quad (10)$$
By providing the value differences as additional features, not only could the model consider the current model’s outputs, but it also could leverage the changes in the model outputs from the previous epoch. These additional features help DAPPER predict the change in performance. We conduct an ablation study to investigate the effectiveness of our features (Conf, Div, Dist, Diff_Conf, Diff_Div, and Diff_Dist) in §5.3.

**Model:** We utilize a conventional LSTM network [19] for the architecture. LSTM is a widely-adopted neural-network architecture in modeling sequential tasks, thanks to its robustness to the vanishing gradient problem in taking long sequences as inputs. We adopt LSTM as our model adaptation process is sequential (e.g., 100 training epochs), and leveraging previous “states” of the model would provide hints to the current accuracy estimation. Specifically, we use three stacks of LSTM layers with 100 hidden dimensions, followed by two fully connected layers with one Dropout activation. We use an L1 loss to minimize the difference between the predicted change in accuracy and the ground-truth change in accuracy (Equation (3)). For optimization, we adopt Adam optimizer [25] with a learning rate of 0.00005. The resulting model is lightweight (835 KB), incurring negligible memory and computation overhead. We conduct a comprehensive analysis for the computation overhead in §5.6.

### 4 EXPERIMENT SETTINGS

#### 4.1 Datasets and Preprocessing

We evaluated our method with the following four real-world mobile sensing datasets.

4.1.1 HHAR. Heterogeneity Human Activity Recognition (HHAR) [58] was collected from nine users, each carrying 12 devices (eight smartphones and four smartwatches). Smartphones were kept in a tight pouch near their waist, while smartwatches were on their arms. Six activity classes were recorded. Devices varied in terms of the maximum sampling rate, sensor specifications, etc. We combined the data from duplicate models and removed two users who do not have the Samsung Galaxy Gear data, resulting in seven users and five devices. We used the 256-length, 50% overlapping window, which is the same as in the original paper [58]. For the domain adaptation task, we randomly chose four users and three devices and combined them as sources (12 domains), and the remaining devices and users were used as targets (six domains).

4.1.2 WESAD. Wearable Stress and Affect Detection (WESAD) [53] is a multi-modal dataset. It was collected from 15 users equipped with the same medical devices around their chest and wrist. WESAD includes diverse sensing modalities: three-axis acceleration, electrocardiogram, electrodermal activity, electromyogram, respiration, body temperature, and blood volume pulse. There are four affective classes in WESAD. We used the lowest sampling rate of 4 Hz in electrodermal activity and down-sampled the others for consistency, which is the same as the previous study [14]. We used a two-second window for training. There are a total of 15 domains. We randomly chose 10 domains as sources and the remaining five domains as targets.

4.1.3 ICHAR. Individual-Condition Human Activity Recognition (ICCHAR) [15] was collected under 10 different users and devices, which counts up to 10 domains. Each participant was holding a smartphone or wearing a unique smartwatch, meaning that each had a device different from the others. There are nine activities. Considering that each participant had a unique device and there was no restriction on how to hold the device, adapting to a new domain in ICHAR would be more challenging than in HHAR. We used a 256-length window following the original paper [15]. There are 10 individual conditions, i.e., domains. We randomly chose 10 domains as sources and the remaining five domains as targets.

4.1.4 ICSR. Individual-Condition Speech Recognition (ICSR) [15] was collected under the same condition as ICHAR. Unlike ICHAR, the task was to speak out 14 different words. Each subject held one unique device in
a preferred way and spoke each word with their own loudness, pitch, and so on. There are 10 domains. We randomly chose seven domains as sources and the remaining three domains as targets.

4.2 Adaptation Methods

To evaluate DAPPER, we generated test data with adaptation algorithms. We considered a common multi-source DA scenario: for each target domain, we pre-trained a base model with the source domains, and the base model was adapted to the target domain. We experimented with two common adaptation scenarios as follows.

4.2.1 SDA. Supervised Domain Adaptation (SDA) utilizes labeled data from a target domain for adaptation. We used a well-known fine-tuning method for SDA where a pre-trained model updated its parameters with a few labeled data from the target domain. Specifically, we randomly chose a target domain first and selected $1 \sim 50$ random labeled data from the target with which we performed adaptation. This process was repeated 50 times for each dataset, and we report the average.

4.2.2 UDA. Unsupervised Domain Adaptation (UDA) aims to adapt to a target domain with only unlabeled data from the target. In our experiments, we used Source HypOthesis Transfer (SHOT) [32], a state-of-the-art UDA algorithm that does not require source data in adaptation. As the source data might not be available to the target users, we believe SHOT is more practical than other UDA methods. Similarly, we chose a target domain randomly, selected $50 \sim 500$ random unlabeled data from the target, and performed adaptation, which was repeated 50 times for each dataset. We provided more samples in UDA than SDA, considering that labeled data is more expensive to collect.

4.2.3 Implementation. For model architecture, we adopted 1D convolutional neural networks (CNN) [26] followed by fully-connected layers, which are commonly used in mobile sensing [3, 15, 24, 51]. We used Rectified Linear Unit (ReLU) [42] for activation function and Batch Normalization layer [21] after each CNN layer for regularization and fast convergence. We used L2-regularization [43] as a regularization technique. We trained the model with Adam optimizer [25]. We used a fixed learning rate of 0.0001 or 0.001 depending on the datasets. We used a conventional standardization for preprocessing the datasets. We used the PyTorch framework [45] for implementation and trained the model with NVIDIA TITAN Xp GPUs. We ran each training for 100 epochs in both adaptation scenarios.

4.3 Baselines

We implement four baselines as follows to evaluate how effective DAPPER is.

4.3.1 TgtLabel. TgtLabel computes accuracy with labeled target validation data. While this performance validation is often used in domain adaptation research [6, 9, 15, 23, 34, 61, 62, 68, 69, 71], always having such labeled data for all target domains is unrealistic. We use TgtLabel as the ground-truth performance.

4.3.2 FixedEpoch. Training until a fixed number of epochs (FixedEpoch) is a widely used model selection method [2, 7, 10, 11, 20, 28, 32, 35, 55, 59, 67, 70, 81]. Note that as FixedEpoch always chooses the last epoch’s model without any validation data, it does not have performance validation.

4.3.3 SrcLabel. Validating performance with labeled source data (SrcLabel) is also a popular method [13, 30, 31, 52] as source data are more likely labeled with a larger amount, compared with target data. SrcLabel computes accuracy from a hold-out labeled source data to estimate the target performance. In order not to affect the performance of the pre-trained model, the hold-out source data for validation were never used in the training process for other baselines as well.
Table 1. Comparison of the baselines and DAPPER.

| Source data | Target data | Extra Training | Performance Val. |
|-------------|-------------|----------------|------------------|
| TgtLabel    | X           | Labeled        | X                |
| FixedEpoch  | X           | X              | X                |
| SrcLabel    | Labeled     | X              | X                |
| DIR [5]     | Labeled     | Unlabeled      | O                |
| DAPPER (ours) | Unlabeled   | X              | O                |

4.3.4 DIR. A recent study utilizes Domain-Invariant Representations (DIR) for estimating generalization under domain shifts [5]. This study learns an accurate “check” model with domain-invariant representations as a proxy for estimating performance. Specifically, it pre-trains a check model with unlabeled target data via DANN [12]. After each adaptation, to estimate performance, it updates the check model that maximizes disagreement with the adapted model. An estimated proxy risk is the maximum disagreement between the check model and the adapted model. Therefore, this algorithm requires updating the check model for every update of the adapted model. We used this proxy risk to calculate an estimated accuracy. For the check model, we used the same model as the adaptation model and used the unlabeled target validation data to train. The check model was updated for 20 epochs as in the original paper [5].

4.3.5 Comparison. Table 1 compares the baselines and DAPPER. “Source data” means whether it requires hold-out source data for performance estimation, and “Target data” means whether it requires target data for estimation. “Labeled” means the requirement of labeled data, “Unlabeled” means the requirement of unlabeled data, and “X” means no requirement of data for that category. “Extra Training” is whether it requires additional training for every updated model. Note that DAPPER requires training only once before deployment, without additional training for every adapted model. “Performance Val.” is whether the method includes performance validation. FixedEpoch does not have performance validation.

In the context of mobile sensing, no previous work has proposed performance estimation utilizing unlabeled data. Most studies train until a fixed number of epochs (FixedEpoch) [10, 20, 81], while several studies have selected the best models on the labeled target validation data (TgtLabel) [15, 69].

4.4 Evaluation Metric

We use similarity calculated from an L1 distance as a metric to compare with baselines. L1 distance, also known as Manhattan Distance, is a metric that calculates the distance between two N dimensional vectors. We regard the true accuracy (TgtLabel) as the oracle and calculate the L1 distance between the ground truth and the estimations. We evaluate the difference between the estimated performance and the oracle by getting the average of L1 distances between two values at each epoch and subtracting the averaged L1 distance from 1 to compute similarity. Specifically, we define similarity as follows:

\[
\text{Similarity} = 1 - \frac{1}{|E|} \sum_{e \in E} \left| \Delta a^{(e)} - \Delta \hat{a}^{(e)} \right|,
\]

which ranges from 0 to 1 (0∼100%). Therefore, the higher the similarity, the better the estimation.

5 EVALUATION

5.1 Overall Results

Table 2 shows the overall results. We randomly selected 500 samples for validation, and those samples were consistent among the methods for a fair evaluation. For instance, TgtLabel and DAPPER used the same 500 samples from a target for validation, but those samples were labeled for TgtLabel and unlabeled for DAPPER.
Table 2. Average similarities (%) of the baselines and DAPPER with four datasets under SDA and UDA.

|             | SDA          | UDA          |
|-------------|--------------|--------------|
|             | HHAR WESAD   | HHAR WESAD   |
| TgtLabel    | 100.0        | 100.0        |
| FixedEpoch  | N/A          | N/A          |
| SrcLabel    | 76.6         | 84.4         |
| DIR         | 67.1         | 71.3         |
| DAPPER      | 95.6         | 92.2         |

SrcLabel used 500 samples from the hold-out source data. For each dataset and adaptation algorithm (SDA or UDA) pair, the result is averaged over 50 training episodes. This comprehensive result shows how effective DAPPER is compared with the baselines and the oracle (TgtLabel). The best values among different methods are highlighted in bold except for TgtLabel. Similarity in TgtLabel is 100, as it is the ground truth. Measuring similarity is not available in FixedEpoch, and thus marked as “N/A.”

The estimation by SrcLabel is often poor as it assumes the target performance is generalizable by hold-out source data without any information from the target. Interestingly, the performance estimations by DIR are in general worst due to their assumption that often fails (details in §5.2). Overall, DAPPER outperforms the baselines, which shows the effectiveness of the proposed proxies coupled with our training methodology for performance estimation. We conduct qualitative analysis to understand further the behaviors of different methods in §5.2.

5.2 Qualitative Analysis

We investigate how similar the estimated performance is to the true performance via qualitative analysis. Figure 10 compares three different methods (SrcLabel, DIR, and DAPPER) to TgtLabel under three different performance patterns: increasing accuracy, decreasing accuracy, and fluctuating accuracy. FixedEpoch is excluded as it does not estimate the performance and simply selects the last epoch’s model. While the other baselines directly predict the accuracy, DAPPER predicts relative accuracy change. We add the true accuracy at epoch zero to the estimated accuracy by DAPPER for better visualization.

The estimated performance by SrcLabel generally decreases as training proceeded, regardless of whether the actual performance improved or not. This means validation with hold-out source data could not apply to unseen targets due to domain shifts. Thus, the estimated performance decreases as the model adapts to the target data. The estimations by DIR are noisy as it requires updating the check model for every epoch. Since the learned representations change as the training continues, the estimations fluctuate accordingly. More importantly, DIR assumes an accurate check model is available [5]. We found that this assumption often does not hold in mobile sensing, where numerous factors affect the performance, resulting in inaccurate estimations.

DAPPER predicts accuracy better than the other baselines in general. As DAPPER relies on the target data to estimate the performance, it does not have the domain shift issue of SrcLabel mentioned above. Moreover, DAPPER uses a pre-trained estimator for performance estimation and does not incur noisy estimations as DIR.

5.3 Ablation Study

We conduct ablative experiments on DAPPER to analyze the effectiveness of the estimator features described in §3.3.2. Figure 11 is the ablation study on the feature modalities used in training DAPPER. We sequentially add features (Conf, Div, and Dist) and compare the average similarities. As our suggested features are added, average similarities become higher in general. This shows the effectiveness of our features for training the estimator.
Figure 10 shows how effective using both the original and the difference values as features is for performance estimation. Original represents using the original values of the features (Conf, Div, and Dist), while Difference refers to using the difference from the previous values (Diff_Conf, Diff_Div, and Diff_Dist). Both means using both feature sets. Note that Both significantly improves the similarity compared to Original and Difference. This implies the importance of considering both the exact value of the features and the difference of them from the previous epoch at the same time for accurate performance estimation.
5.4 Impact of Validation Data Distribution

In §5.1, we used 500 randomly sampled validation data, which naturally follows the target data distribution. However, in practice, it is possible to have imbalanced target validation data. Taking human activity recognition for instance, one could stay home during sick leaves, which would contain more static activities (sleeping, sitting, etc.) than dynamic activities. In this case, performance estimation would be conducted under skewed validation data. We investigate how resilient DAPPER is on such an imbalanced distribution of target validation data. Specifically, for each dataset, we randomly selected half of the classes and dropped 20%, 40%, 60%, and 80% out of the 500 samples for the selected classes. The number of samples used for validation decreases accordingly.

Figure 13 shows the results with different distributions of the validation data. Here, we set the TgtLabel with balanced data (0%) as the optimum and calculated the average similarity with respect to that optimum. Note that TgtLabel is also affected by the target data distribution; even if we use the labeled target data, the estimation becomes gradually inaccurate as data distribution becomes imbalanced. To some extent of imbalance, DAPPER shows relatively stable performance. Interestingly, we found that the gap of the average similarity between 0% and 80% is better in DAPPER than TgtLabel (5% in DAPPER and 7% in TgtLabel). We conjecture that this robustness is attributed to the use of TgtLabel by considering the relative changes from the previous features rather than merely focusing on absolute values. Nevertheless, under extreme cases (80% drop), the average similarity dropped. By diversifying the training data (e.g., training with imbalanced virtual-target validation data)
in training estimator, we believe DAPPER could be more resilient to the imbalanced distribution, which we leave as future work.

5.5 Impact of Number of Training Data

We generate simulated adaptation data with the source data to train DAPPER. Note that this training dataset could be almost infinitely created via randomness. Still, as practical guidance, it would be worth understanding how the number of training data impacts performance estimation. Figure 14 shows the result with varying the number of training data from 100 to 10,000. While the result depends on datasets, an interesting finding is that DAPPER could learn with a small amount of data (e.g., 100). A rule of thumb to select the number of training data could be training with as diverse data as possible. We trained DAPPER with 10,000 data in the other experiments.

5.6 Computation Overhead

On-device deep learning has been increasingly important owing to its advantages over central training. A variety of private information such as location, health states, emotions, and identifiable information, could be inferred by leaking personal sensing data [27, 66], which could be protected via on-device training. Additionally, on-device training can save communication bandwidth and the cloud management cost [8, 79]. We inspect the computation overhead of DAPPER and the baselines in terms of on-device training and inference.

We implemented the training algorithms (SDA and UDA), the baselines, and DAPPER with the Mobile Neural Network (MNN) framework by Alibaba [22]. MNN supports both training and inference and achieves state-of-the-art performance with optimized assembly code. We used three smartphones (Google Pixel 5, Google Pixel 2, and LG Nexus 5) for this experiment. We reproduced the experiment with the HHAR dataset under those mobile devices to measure the computational overhead. Both training and inference were made through the CPU with four threads.

We consider the computation overhead in two aspects: (i) computation overhead per epoch and (ii) computation overhead until the best-performance epoch (BestEpoch). While the former reveals the computation overhead for each performance estimation, the latter calculates the total computation overhead until it reaches the best performance. The latter could tell whether the performance estimators could reduce computation overhead over training until a fixed number of epochs; i.e., the computation overhead could be reduced by early stopping the training if the estimated performance is no longer improved or less than a predefined threshold, according to its implementation. For each case, we measured the computation overhead 20 times and reported the average computation time.

Figure 15 presents the result. The error bar is the standard deviation. Figure 15a shows the computation time required for each epoch. FixedEpoch is excluded as it does not have additional computation. SDA and UDA refer
to the training time required to update the model for each epoch. Note that the computation time of DIR is even higher than SDA and UDA due to the check model update. Since only one forward pass is necessary for TgtLabel and SrcLabel, they show almost the same result. TgtLabel, SrcLabel, and DAPPER show negligible computation time compared with the training cost in SDA and UDA. We found that DAPPER’s average computation latency was 3.5 ms, which is comparable to that of TgtLabel and SrcLabel (3.1 ms). Additional computation overhead caused by the inference on the estimator network was only around 0.4 ms on mobile devices, thanks to the lightweight model (835 KB).

Figure 15b shows the computation time required until BestEpoch. Note that BestEpoch of FixedEpoch is 100 as it trains until the end. FixedEpoch shows a higher computation time (2.5~3.2x) than DAPPER. It suggests that performance estimation could reduce computation overhead drastically by early stopping. The method that requires extra training (DIR) still involved high computational overhead with fewer epochs than FixedEpoch, which is 4~84x higher than FixedEpoch and 14~216x higher than DAPPER. This implies that regardless of the accuracy of estimation, a method that requires extra training in the user side might incur a large computational overhead. In summary, not only DAPPER accurately estimates performance, but it also generates affordable computation overhead as similar as TgtLabel. Moreover, DAPPER utilizes only unlabeled data that could be collected without users’ manual effort.

6 RELATED WORK

6.1 Validation Methods in Domain Adaptation

We review how existing domain adaptation (DA) methods selected their model and reported the performance. For the papers that do not specify their validation method, we referred to their implementation, e.g., on a GitHub repository.

Many domain adaptation proposals used labeled target data for selecting the best model and reported the best performance [6, 9, 23, 34, 61, 62, 68, 71]. While it could be meaningful to report theoretically “achievable” performance, we believe that labeled target data would not be available for every single target in practical deployments. Another approach in DA is to train until a fixed number of epochs (e.g., 100) and report the last epoch’s performance [2, 7, 11, 28, 32, 35, 55, 59, 67, 70]. However, as the number of epochs was selected empirically, it could lead to performance degradation or unnecessary training overhead for unseen targets, as we examined in §2.1. Another popular method is to select the best model on a hold-out source dataset (often with early stopping) [13, 30, 31, 52]. However, it would fail when target domains deviate from the hold-out source data. Domain adaptation for mobile sensing shows similar trends. While most studies adopted training until a fixed number of epochs [10, 20, 81], several studies selected the best models on the labeled target validation data [15, 69].
6.2 Performance Estimation with Unlabeled Data

Some schemes utilize unlabeled data for performance estimation but require assumptions that might not hold in mobile sensing scenarios. Limberg et al. [33] estimated the accuracy of four target machine learning classifiers (Support Vector Machine, Random Forest Classifier, k-Nearest Neighbors, and Generalized Vector Quantization) with a semi-supervised approach for robot object recognition tasks. However, it was experimentally shown that it worked well only when the training and test conditions are the same, which might not be applicable in heterogeneous mobile sensing. Platonis et al. [46] estimated accuracy with unlabeled data by the agreement of multiple boolean functions. Their subsequent work [47] improved estimation accuracy given logical constraints among classes. However, both studies were limited to binary classifiers and might be difficult to extend to general multi-class classifiers. Steinhardt et al. [57] estimated unsupervised risk (error) with unlabeled data by assuming three conditionally independent views of a sample are available, which limits the practicality of its approach.

Several studies utilized deep learning to estimate the performance under domain shifts [5, 74]. Deep Embedded Validation (DEV) [74] proposed a model selection method with estimating the ratio between the source and the target density (i.e., density ratio). Specifically, DEV predicts the target risk by training a domain discriminator from the unlabeled target data and estimating the density ratio. However, DEV assumes that a well-adapted model is available that shows lower distribution divergence in the feature space, and thus it often fails to estimate the target risk accurately. In fact, the risk can grow to infinity, especially when the model is not adapted well.

DIR [5] is the state-of-the-art performance estimation method under domain shift. DIR estimates the target performance via a “check model.” DIR maximizes the disagreement between the check model and an adapted model to estimate the target risk. DIR requires training the check model with the unlabeled target data via DANN algorithm [12]. Similar to DEV, DIR assumes that the check model is accurate, which might not hold in reality. Note that both DEV and DIR require additional training after deployment for training the domain discriminator and the check model, respectively. As DEV focuses on the model selection and does not provide a comparable performance metric, we compared DAPPER with DIR.

7 DISCUSSION

7.1 Training and Validation Data Split

In our experiments, we used 500 validation data (less than 500 in the experiments with imbalanced data) for performance estimation. While we focused on performance estimation with unlabeled data, the ratio between training and validation data could be an important decision, especially for real deployments. For instance, given 1,000 unlabeled data collected from a target user, the ratio between the number of training and validation samples could affect both the model’s accuracy and the estimation accuracy. Furthermore, when only a few labeled data instances are available, utilizing some of them along with unlabeled data could improve performance estimation. Note that there is a trade-off in selecting the ratio between the training data and validation data; a larger number of training data would result in better adaptation, while a larger number of validation data would provide better estimation, as shown in §5.4. This is a similar discussion to the efficient training/validation data split in machine learning [49, 75], and their valuable findings could provide insights into our mobile sensing scenarios.

7.2 Continuous Data Stream

We focused on predicting the performance within a single adaptation episode given a set of train/validation data. However, there could be continuous sensor data streams from the target users in the real world. We argue that the importance of performance validation becomes even more important in such scenarios, as it might involve multiple adaptations with the new data. We believe our insights and findings from this work could be applicable to the continuous data stream case. However, issues that need to be addressed remain, such as how to deal with distribution shifts as time passes, how many data can be kept, what data should be discarded, etc.
8 CONCLUSION

We investigated the uncertainty of domain adaptation performance in mobile sensing and the importance of performance validation. As a solution, we proposed DAPPER, a performance estimation framework that utilizes only unlabeled data from a target domain. As unlabeled data are collected naturally in mobile sensing, it does not require additional manual user effort for labeling. Our evaluation with four real-world sensing datasets showed that DAPPER is the most accurate performance estimator compared to the baselines. In addition, our on-device computation analysis showed that we reduced the computation overhead up to 216× compared with the existing training-based estimation. We believe our study discloses an important problem of performance estimation in mobile sensing domain adaptation and proposes a viable solution that takes a meaningful step towards overcoming the performance dynamics in mobile sensing.
REFERENCES

[1] Sourav Bhattacharya, Petteri Nurmi, Nils Hammerla, and Thomas Platzer. 2014. Using unlabeled data in a sparse-coding framework for human activity recognition. *Pervasive and Mobile Computing* 15 (2014), 242–262. https://doi.org/10.1016/j.pmcj.2014.05.006

[2] Fabio M. Carlucci, Antonio D’Innocente, Silvia Bucceri, Barbara Caputo, and Tatiana Tommasi. 2019. Domain Generalization by Solving Jigsaw Puzzles. In *2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*. IEEE, New York City, 2224–2233. https://doi.org/10.1109/CVPR.2019.00233

[3] Youngjae Chang, Akhil Mathur, Anton Isopoussu, Junehwa Song, and Fahim Kawarz. 2020. A Systematic Study of Unsupervised Domain Adaptation for Robust Human-Activity Recognition. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 4, 1, Article 39 (March 2020), 30 pages. https://doi.org/10.1145/3380985

[4] Jagmohan Chauhan, Jathushan Rajasegaran, Suranga Seneviratne, Archan Misra, Aruna Seneviratne, and Youngki Lee. 2018. Performance Characterization of Deep Learning Models for Breathing-Based Authentication on Resource-Constrained Devices. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 2, 4, Article 158 (Dec. 2018), 24 pages. https://doi.org/10.1145/3287036

[5] Ching-Yao Chuang, Antonio Torralba, and Stefanie Jegelka. 2020. Estimating Generalization under Distribution Shifts via Domain-Invariant Representations. *International conference on machine learning* (2020).

[6] Shuhao Cui, Shuhui Wang, Junbao Zhuo, Chi Su, Qingming Huang, and Qi Tian. 2020. Gradually Vanishing Bridge for Adversarial Domain Adaptation. In *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*. IEEE, New York City, 2452–2461. https://doi.org/10.1109/CVPR42600.2020.01247

[7] Bharath Bhushan Damodaran, Benjamin Kellenberger, Rémi Flamary, Devis Tuia, and Nicolas Courty. 2018. DeepIDOT: Deep Joint Distribution Optimal Transport for Unsupervised Domain Adaptation. In *Computer Vision – ECCV 2018*, Vittorio Ferrari, Martial Hebert, Cristian Sminchisescu, and Yair Weiss (Eds.). Springer International Publishing, Cham, 467–483.

[8] Yunbin Deng. 2019. Deep learning on mobile devices: a review. In *Mobile Multimedia/Image Processing, Security, and Applications 2019*, Sos S. Agaian, Vijayan K. Asari, and Stephen P. DeMarco (Eds.), Vol. 10993. International Society for Optics and Photonics, SPIE, 52–66. https://doi.org/10.1117/12.2518469

[9] Qi Dou, Daniel Coelho de Castro, Konstantinos Kamnitsas, and Ben Glocker. 2019. Domain Generalization via Model-Agnostic Learning of Semantic Features. In *Advances in Neural Information Processing Systems*, H. Wallach, H. Larochelle, A. Beygelzimer, F. d’Alché-Buc, E. Fox, and R. Garnett (Eds.), Vol. 32. Curran Associates, Inc. https://proceedings.neurips.cc/paper/2019/file/2974788b53f73e7950e98a1a49fa3a06db-Paper.pdf

[10] Baiying Fu, Naser Damer, Florian Kirchbuchner, and Arjan Kuiper. 2021. Generalization of Fitness Exercise Recognition from Doppler Measurements by Domain-Adaption and Few-Shot Learning. In *Pattern Recognition. ICPR International Workshops and Challenges*, Alberto Del Bimbo, Rita Cucchiara, Stan Sclaroff, Giovanni Maria Farinella, Tao Mei, Marco Bertini, Hugo Jair Escalante, and Roberto Vezzani (Eds.). Springer International Publishing, Cham, 203–218.

[11] Yaroslav Ganin and Victor Lempitsky. 2015. Unsupervised Domain Adaptation by Backpropagation. In *Proceedings of the 32nd International Conference on International Conference on Machine Learning - Volume 37* (Lille, France) (ICML’15). JMLR.org, 1180–1189.

[12] Yaroslav Ganin, Evgeniya Ustinova, Hana Ajakan, Pascal Germain, Hugo Larochelle, François Laviolette, Mario Marchand, and Victor Lempitsky. 2016. Domain-Adversarial Training of Neural Networks. *J. Mach. Learn. Res.* 17, 1 (Jan. 2016), 2096–2030.

[13] Muhammad Ghifary, W. Bastiaan Kleijn, Mengjie Zhang, and Wen Li. 2016. Deep Reconstruction-Classification Networks for Unsupervised Domain Adaptation. In *Computer Vision – ECCV 2016*, Bastian Leibe, Jiri Matas, Nicu Sebe, and Max Welling (Eds.). Springer International Publishing, Cham, 597–613.

[14] Taesik Gong, Yeonsoo Kim, Ryyuhaerang Choi, Jinwoo Shin, and Sung-Ju Lee. 2021. Adapting to Unknown Conditions in Learning-based Mobile Sensing. *IEEE Transactions on Mobile Computing* (2021), 1–1. https://doi.org/10.1109/TMC.2021.3061130

[15] Taesik Gong, Yeonsoo Kim, Jinwoo Shin, and Sung-Ju Lee. 2019. MetaSense: Few-Shot Adaptation to Untrained Conditions in Deep Mobile Sensing. In *Proceedings of the 17th Conference on Embedded Networked Sensor Systems (SenSys ’19)*. Association for Computing Machinery, New York, NY, USA, 110–123. https://doi.org/10.1145/3356250.3360020

[16] Yves Grandvalet and Yoshua Bengio. 2004. Semi-Supervised Learning by Entropy Minimization. In *Advances in Neural Information Processing Systems 17*, Yves Grandvalet and Yoshua Bengio (Eds.). Curran Associates, Inc. https://proceedings.neurips.cc/paper/2004/file/17f118327e54270b7405b8f2567f5d8b-Paper.pdf

[17] Chuan Guo, Geoff Pleiss, Yu Sun, and Kilian Q. Weinberger. 2017. On Calibration of Modern Neural Networks. In *Proceedings of the 34th International Conference on Machine Learning (Proceedings of Machine Learning Research, Vol. 70)*. Doina Precup and Yee Whye Teh (Eds.). PMLR, 1321–1330. http://proceedings.mlr.press/v70/guo17a.html

[18] Tin Kam Ho and M. Basu. 2002. Complexity measures of supervised classification problems. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 24, 3 (2002), 289–300. https://doi.org/10.1109/34.990132

[19] Sepp Hochreiter and Jurgen Schmidhuber. 1997. Long Short-Term Memory. *Neural Computation* 9, 8 (1997), 1735–1780. https://doi.org/10.1162/neco.1997.9.8.1735
Charissa Ann Ronao and Sung-Bae Cho. 2016. Human activity recognition with smartphone sensors using deep learning neural networks. In Proceedings of the twenty-first international conference on machine learning (Banff, Alberta, Canada) (ICML ’04). Association for Computing Machinery, New York, NY, USA, 780–787.

Andrew Y. Ng. 2004. Feature Selection, L1 vs. L2 Regularization, and Rotational Invariance. In Proceedings of the Twenty-First International Conference on Machine Learning (Banff, Alberta, Canada) (ICML ’04). Association for Computing Machinery, New York, NY, USA, 780–787. https://doi.org/10.1145/1015330.1015435

Bahatunde Kazeem Olorisade, Pearl Brereton, and Peter Andras. 2017. Reproducibility of studies on text mining for citation screening in systematic reviews: Evaluation and checklist. Journal of Biomedical Informatics 73 (2017), 1–13. https://doi.org/10.1016/j.jbi.2017.07.010

Emmanouil Antonios Platanios, Avrim Blum, and Tom Mitchell. 2014. Estimating Accuracy from Unlabeled Data. In Proceedings of the Thirtieth Conference on Uncertainty in Artificial Intelligence (Quebec City, Quebec, Canada) (UAI’14). AUAI Press, Arlington, Virginia, USA, 682–691.

Emmanouil Antonios Platanios, Hoifung Poon, Tom M. Mitchell, and Eric Joel Horvitz. 2017. Estimating Accuracy from Unlabeled Data: A Probabilistic Logic Approach. In Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems 2017, December 4-9, 2017, Long Beach, CA, USA, Isabelle Guyon, Ulrike von Luxburg, Samy Bengio, Hanna M. Wallach, Rob Fergus, S. V. N. Vishwanathan, and Roman Garnett (Eds.). 4361–4370. https://proceedings.neurips.cc/paper/2017/hash/95f8d9901ca8878e291552f001f67692-Abstract.html

Valentin Radu, Catherine Tong, Sourav Bhattacharyya, Nicholas D. Lane, Cecilia Mascolo, Mahesh K. Marina, and Fahim Kawsar. 2018. Multimodal Deep Learning for Activity and Context Recognition. Proc. ACM Interact. Mob. Wearable Ubiquitous Technol. 1, 4, Article 157 (Jan. 2018), 27 pages. https://doi.org/10.1145/3161174

Zuzana Reitermanova. 2010. Data splitting. In WDS, Vol. 10. 31–36.

Charissa Ann Ronao and Sung-Bae Cho. 2016. Human activity recognition with smartphone sensors using deep learning neural networks. Expert Systems with Applications 59 (2016), 235–244. https://doi.org/10.1016/j.eswa.2016.04.032

Aaqib Saeed, Tanir Ozcelebi, and Johan Lukkien. 2019. Multi-Task Self-Supervised Learning for Human Activity Detection. Proc. ACM Interact. Mob. Wearable Ubiquitous Technol. 3, 2, Article 61 (June 2019), 30 pages. https://doi.org/10.1145/3328932

Swami Sankaranarayanan, Yosheg Balaji, Carlos D. Castillo, and Rama Chellappa. 2018. Generate to Adapt: Aligning Domains Using Generative Adversarial Networks. In 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition. 8503–8512. https://doi.org/10.1109/CVPR.2018.00887

Philip Schmidt, Attila Reiss, Robert Duerichen, Claus Marberger, and Kristof Van Laerhoven. 2018. Introducing wesad, a multimodal dataset for wearable stress and affect detection. In Proceedings of the 20th ACM International Conference on Multimodal Interaction. 400–408.

C. E. Shannon. 1948. A Mathematical Theory of Communication. Bell System Technical Journal 27, 3 (1948), 379–423. https://doi.org/10.1002/j.1538-7305.1948.tb01338.x

Rui Shu, Hung Bui, Hirokazu Narui, and Stefano Ermon. 2018. A DIRT-T Approach to Unsupervised Domain Adaptation. In International Conference on Learning Representations. https://openreview.net/forum?id=H1q-TM-AW

Andrea Soro, Gino Brunner, Simon Tanner, and Roger Wattenhofer. 2019. Recognition and Repetition Counting for Complex Physical Exercises with Deep Learning. Sensors 19, 3 (2019). https://doi.org/10.3390/s19030714

Jacob Steinhardt and Percy S Liang. 2016. Unsupervised Risk Estimation Using Only Conditional Independence Structure. In Advances in Neural Information Processing Systems, D. Lee, M. Sugiyama, U. Luxburg, I. Guyon, and R. Garnett (Eds.), Vol. 29. Curran Associates, Inc., 8024–8035. http://papers.neurips.cc/paper/9015-pytorch-an-imperative-style-high-performance-deep-learning-library.pdf

J. ACM, Vol. 0, No. 0, Article 0. Publication date: 2021.
[59] Baochen Sun and Kate Saenko. 2016. Deep CORAL: Correlation Alignment for Deep Domain Adaptation. In Computer Vision – ECCV 2016 Workshops, Gang Hua and Hervé Jégou (Eds.). Springer International Publishing, Cham, 443–450.

[60] Chi Ian Tang, Ignacio Perez-Pozuelo, Dimitris Spadis, Soren Brage, Nick Wareham, and Cecilia Mascolo. 2021. SelfHAR. Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies 5, 1 (Mar 2021), 1–30. https://doi.org/10.1145/3448112

[61] Hui Tang, Ke Chen, and Kui Jia. 2020. Unsupervised Domain Adaptation via Structurally Regularized Deep Clustering. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). IEEE, New York City, 8725–8735.

[62] Hui Tang and Kui Jia. 2020. Discriminative Adversarial Domain Adaptation. In Association for the Advancement of Artificial Intelligence (AAAI).

[63] Yunus Emre Ustev, Oulem Durmaz Incel, and Cem Ersoy. 2013. User, Device and Orientation Independent Human Activity Recognition on Mobile Phones: Challenges and a Proposal. In Proceedings of the 2013 ACM Conference on Pervasive and Ubiquitous Computing. Adjunct Publication (Zurich, Switzerland) (UbiComp ’13 Adjunct). Association for Computing Machinery, New York, NY, USA, 1427–1436. https://doi.org/10.1145/2494091.2496039

[64] Tuan-Hung Vu, Himalaya Jain, Maxime Perez-Pozuelo, Dimitris Spadis, Soren Brage, Nick Wareham, and Cecilia Mascolo. 2021. DAPPER: Performance Estimation of Domain Adaptation in Mobile Sensing. AAAI Press, 6502–6509.
[78] Hanbin Zhang, Chenhan Xu, Huining Li, Aditya Singh Rathore, Chen Song, Zhisheng Yan, Dongmei Li, Feng Lin, Kun Wang, and Wenyao Xu. 2019. PDMove: Towards Passive Medication Adherence Monitoring of Parkinson’s Disease Using Smartphone-Based Gait Assessment. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 3, 3, Article 123 (Sept. 2019), 23 pages. https://doi.org/10.1145/3351281

[79] Yu Zhang, Tao Gu, and Xi Zhang. 2020. MDLdroid: a ChainSGD-reduce Approach to Mobile Deep Learning for Personal Mobile Sensing. In *2020 19th ACM/IEEE International Conference on Information Processing in Sensor Networks (IPSN)*. 73–84. https://doi.org/10.1109/IPSN48710.2020.00-45

[80] Bing Zhou, Jay Lohokare, Ruipeng Gao, and Fan Ye. 2018. EchoPrint: Two-Factor Authentication Using Acoustics and Vision on Smartphones. In *Proceedings of the 24th Annual International Conference on Mobile Computing and Networking* (New Delhi, India) (*MobiCom ’18*). Association for Computing Machinery, New York, NY, USA, 321–336. https://doi.org/10.1145/3241539.3241575

[81] Zhijun Zhou, Yingtian Zhang, Xiaojing Yu, Panlong Yang, Xiang-Yang Li, Jing Zhao, and Hao Zhou. 2020. XHAR: Deep Domain Adaptation for Human Activity Recognition with Smart Devices. In *2020 17th Annual IEEE International Conference on Sensing, Communication, and Networking (SECON)*. 1–9. https://doi.org/10.1109/SECON48991.2020.9158431