PhD Forum Abstract: Integrating Prior Knowledge and Machine Learning Techniques for Efficient AIoT Sensing

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Abstract

Recent advances in machine learning have inspired the development of deep neural network (DNN)-based smart sensing applications for the Artificial Internet of Things (AIoT). However, the effectiveness of DNNs relies on the availability of large, labeled data to uncover useful feature representations. The widespread use of DNN models in computer vision (CV), natural language processing (NLP), and voice sensing can be attributed to the massively available labeled training datasets. Despite the abundance of IoT sensing data, the human-uninterpretable property of AIoT data makes it difficult to construct labeled datasets for DNN model training. Additionally, variations in sensor hardware or DNN models' deployment environments introduce domain shifts, making generalized machine learning algorithms even more difficult to develop. The *scarcity of labeled training data* and *run-time domain shifts* are two main challenges in developing effective machine learning algorithms for AIoT sensing. The goal of my research is to address the above challenges for AIoT sensing applications. Two main research methodologies are involved. The first is to leverage the latest state-of-the-art machine learning techniques to develop effective models for smart sensing. The second approach involves integrating known prior knowledge into machine learning algorithms to develop more accurate and reliable DNN models for AIoT sensing applications.

CCS Concepts

• **Computing methodologies → Neural networks**; *Neural networks*; **Spatial and physical reasoning**.

Keywords

Physics-informed machine learning, Artificial intelligence of things

ACM Reference Format:
Wenjie Luo. 2023. PhD Forum Abstract: Integrating Prior Knowledge and Machine Learning Techniques for Efficient AIoT Sensing. In *The 22nd International Conference on Information Processing in Sensor Networks (IPSN '23), May 9–12, 2023, San Antonio, TX, USA*. ACM, New York, NY, USA, 2 pages. https://doi.org/10.1145/3583120.3589570

IPSN '23, May 9–12, 2023, San Antonio, TX, USA

ACM ISBN 979-8-4007-0118-4/23/05.
https://doi.org/10.1145/3583120.3589570

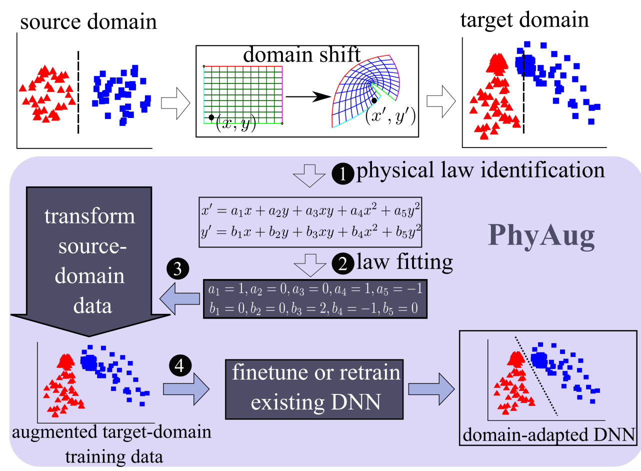

Fig. 1: Physics-informed data augmentation.

1 Physics-Informed Data Augmentation

Run-time domain shift refers to the differences in distribution between the sensor data collected in the wild and the standard training data used to train deep neural network (DNN) models. It is a common phenomenon in AIoT sensing and can lead to degraded performance of pre-trained DNN models. To address this issue, existing studies have employed transfer learning techniques [4], which involve transferring the knowledge of a DNN model learned from the source domain to a target domain. Current methods still require a substantial amount of data to achieve satisfactory performance.

In physics-rich cyber-physical sensing applications, the domain shifts are often governed by certain prior knowledge. Comprehension of such prior knowledge can aid in the creation of more efficient and generalized machine learning models by incorporating prior knowledge as additional information during the model training. We propose an approach called *physics-directed data augmentation* (PhyAug) [3] to address the run-time domain shifts caused by the IoT sensors. Such domain shifts can be described by the parameterized models. For example, the performance of a microphone is characterized by its frequency response curve; a fisheye camera is characterized by a polynomial function, etc. PhyAug utilizes such parameterized models to guide the adaptation of DNN models. Fig. 1 depicts the workflow. First, the system designer identified the physical laws governing the domain shift, which contains unknown parameters. Second, A small amount of data are collected from both the source and target domain to estimate the parameters of the laws. Third, the source-domain data are transformed to the target domain using the fitted law, creating an augmented training dataset. Lastly, The DNN model can be adapted to the target domain using

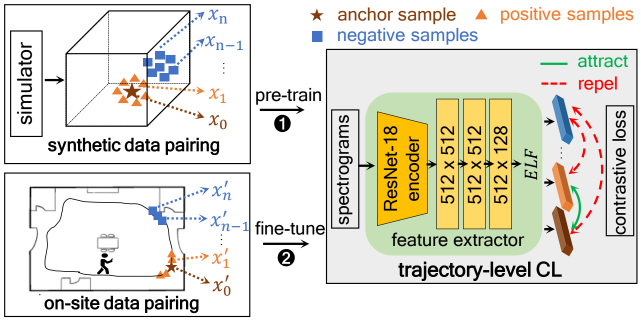

Fig. 2: Contrastive learning procedures for echoic location features construction.

both the source domain and the augmented target domain data, e.g., via model re-training or finetuning. PhyAug has the following two key features. First, PhyAug augments the training data strategically by following the prior knowledge to transfer DNNs instead of using *ad hoc* perturbations or transformations like conventional data augmentation does. Second, PhyAug only requires a small amount of target domain data for physical law fitting. This data requirement is less than the competing baselines that use transfer learning techniques. We apply PhyAug to a series of case studies and measure the performance gains compared with other possible approaches. PhyAug can effectively recover the performance drop caused by sensor variations and outperform the competing baselines. The results highlight the potential of PhyAug in addressing a range of physics-governed domain shifts for various AIoT sensing applications.

2 Self-supervised Feature Learning

AIoT sensing applications are featured in a wealth of unlabeled data. Self-supervised learning can be applied to extract useful feature representations from unlabeled sensing data. By pre-training a DNN model with self-supervised learning, it is possible to fine-tune the model for a specific task using only a small amount of labeled data. This greatly reduces the need for collecting large amounts of labeled training data. The second of my research work enables a smartphone-based SLAM system [2] using the echoic location feature (ELF) learned via a self-supervised learning technique.

In this work, we program a smartphone's loudspeaker to emit near-inaudible chirps in the indoor space and the microphone to capture the acoustic echoes reflected from the surroundings. The echoes carry location information and can be exploited for location sensing. We collect the echoes captured at a certain location to form the fingerprints and train a DNN model for location recognition. However, the blanket process of collecting labeled fingerprints at spatially fine-grained locations to form the training dataset imposes a high overhead. To unleash the fingerprint approach from such blanket labeled data collection, we design a simultaneous localization and mapping (SLAM) system based on the smartphone's inertial measurement unit (IMU) data and the collected echoes. The IMU data is used to obtain an inaccurate user trajectory and the echoes are used to detect loop closures for trajectory rectification.

As a key to SLAM, loop closure detection requires an effective embedding such that the acoustic echoes captured at the same location are close and those from different locations are apart. However, our tests show that the generic features are ineffective for location discrimination. Thus, we opt to learn an effective embedding using a DNN model. Contrastive learning (CL) [1] is a self-supervised learning technique that can learn effective feature representations from unlabeled data. Applying contrastive learning directly to acoustic echoes introduces several issues. Therefore, we make the following customized designs. First, we design a new positive/negative data pairing scheme. Spatial perturbations are often introduced in image recognition to create effective positive data pairs. However, they are inappropriate for echo data as they can potentially destroy the subtle structural information within the echo signal. Our design considers the empirical experience and treats echoes collected at close locations as positive pairs and those collected at distant locations as negative pairs. Second, we eliminate the data collection requirement through the construction of synthetic training data. We use a room acoustic simulator to generate synthetic training data for model training. This helps to reduce the burden of data collection. Third, we use a small amount of unlabeled data collected by users to finetune the pre-trained model, such that it can be adapted to the target room. Our model finetuning only requires a few minutes of unlabeled data and causes little overhead. The procedures of contrastive learning for ELFs construction are illustrated in Fig. 2.

We evaluate our ELF-based SLAM system in three different indoor spaces. Our system achieves sub-meter errors in both trajectory map construction and localization. It outperforms SLAM systems based on the Wi-Fi RSSI and geomagnetic field.

3 Future Work

Physics-informed machine learning (PIML) [5] leverages the known prior knowledge to accelerate model training and improve the performance of machine learning algorithms. PIML has been successfully applied in modeling multi-physical and multi-scale systems. Our PhyAug is an exploration of PIML for AIoT sensing. Considering the potential benefits brought by PIML, we will continue to pursue more efficient approaches in incorporating physical knowledge in machine learning algorithms for AIoT sensing applications.

About author. Wenjie Luo is a Ph.D candidate at the School of Computer Science and Engineering, Nanyang Technological University, Singapore. He started his Ph.D study in 2019 and is expected to graduate in 2023. He is supervised by prof. Rui Tan, who leads the NTU AIoT sensing group. His research interests include Cyber-physical systems and AIoT sensing.

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