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Camouflage learning: Data obscuring ambient intelligence for constrained devices

Le Ngu Nguyen, *Member, IEEE,* Stephan Sigg, *Member, IEEE,* Jari Lietzen, Rainhard Dieter Findling, and Kalle Ruttik, *Member, IEEE*

Abstract—Ambient intelligence demands collaboration schemes for distributed constrained devices which are not only highly energy efficient with respect to distributed sensing, processing and communication, but which also respect data privacy. Traditional algorithms for distributed processing suffer in Ambient intelligence domains either from limited data privacy, or from their excessive processing demands for constrained distributed devices.

In this paper, we present Camouflage learning, a distributed machine learning scheme that obscures the trained model via probabilistic collaboration using physical-layer computation offloading and demonstrate the feasibility of the approach on backscatter communication prototypes and in comparison with federated learning, a popular distributed learning scheme. We show that Camouflage learning is more energy efficient than traditional schemes and that it requires less communication overhead while reducing the computation load through physical-layer computation offloading. The scheme is synchronization-agnostic and thus appropriate for sharply constrained, synchronization-incapable devices. We demonstrate model training and inference on four distinct datasets and investigate the performance of the scheme with respect to communication range, impact of challenging communication environments, power consumption, and the backscatter hardware prototype.

Index Terms—Distributed machine learning, Data obfuscation, Backscatter, Computation offloading, Ambient Intelligence

1 Introduction

The ubicomp and Pervasive computing vision of *computing any time and everywhere* through instrumented and connected environments and objects, has attracted significant attention over the past two decades [1]. Related research on the Internet of Things (IoT) [2], middleware [3], mobile computing [4], sensors [5], [6], microprocessors [7], [8], user interfaces [9], computer networks [10], new materials [11], localization [12] and activity recognition [13] have flourished and advanced this vision.

Computing any time and everywhere demands continuous perception and communication among instrumented objects. This opens challenges with respect to (a) data privacy, (b) extreme energy efficiency for sensing, processing and communication, as well as (c) overhead-less collaboration among constrained devices (cf. figure 1).

To achieve (a), federated learning [14], data obfuscation [15], or homomorphic encryption [16] have been proposed, which demand high processing or communication load or compromise accuracy. *We propose Camouflage Learning*, an efficient and accurate distributed machine learning scheme that obscures the jointly utilized and trained model through non-reversible data aggregation.

Likewise, (b) energy-less operation for sensing, processing and communication has been approached through the development of energy harvesting schemes [17], chemical and organic sensors [18], [19] or, for instance, highly efficient communication schemes, such as LoRa [20], [21]. Our camouflage learning implementation is compatible with any low energy sensor, achieves energy-less computation via *physical-layer computation offloading* and discounts communication cost via backscattering. We show that our scheme outperforms LoRa in energy efficiency for communication.

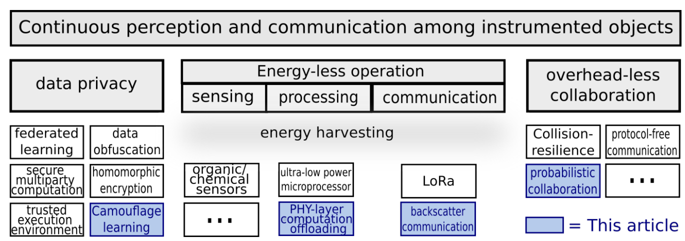

Fig. 1. Concepts and technology to realize the Ubicomp vision of computing to appear anytime and everywhere.

Overhead-less collaboration (c) has been addressed with collision resilient protocols [22] that usually require at least weak synchronization. We utilize *probabilistic collaboration* to dispose synchronization need. Our contributions are:

- A **Camouflage Learning** scheme: distributed machine learning via non-reversible data aggregation (all devices have incomplete model-information).
- **Synchronization agnostic** distributed training and inference via physical layer probabilistic collaboration and wireless channel computation offloading
- A **Proof-of-concept implementation** and evaluation utilizing highly efficient backscatter prototypes
- A **performance comparison** demonstrating higher efficiency than traditional distributed learning.

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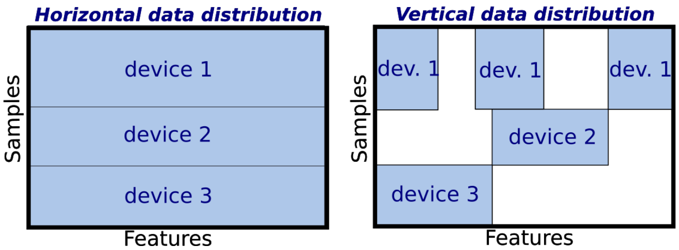


Fig. 2. Horizontal vs. vertical data separation across devices

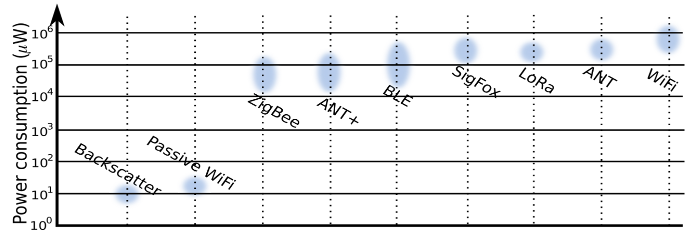


Fig. 3. Energy consumption of various communication technologies

In contrast to existing distributed machine learning, information on the model is scattered across devices (Camouflage Learning). No single device has, at any time, knowledge on the complete model or on other device's data.

2 Related Work

Data science, the extraction of information and patterns from data, has applications in virtually every domain in industry, academia and public [23]. The data d from software or hardware sensors is analyzed with respect to relevant features $\mathbf{x}$ to approximate a target function f that predicts specific target classes $y = f(\mathbf{x})$ [24]. For this, a candidate model $h(\mathbf{x})$ approximates $f(\mathbf{x})$ from the hypothesis space H using historical data for training and testing. The model h combines the weighted features into a mathematical function where the weights $\mathbf{w}$ are chosen such that the errors in the mapping between feature space and target classes are minimized according to the historical data [25].

In Ambient Intelligence, data is collected by distributed sensing devices [26], so that the feature vector $\mathbf{x}$ might be physically spread across the environment. Furthermore, it often contains personal information, that might demand privacy [27] (section 2.1). Furthermore, since energy consumption is of major concern in Ambient Intelligence domains, section 2.2 will discuss advances in energy efficient sensing, processing, and communication. Finally, section 2.3 summarizes low overhead device collaboration mechanisms for Ambient Intelligent environments.

2.1 Distributed Machine Learning and privacy

Classical machine learning assumes a single data set and data distribution, as it is typical in Ambient Intelligence, might require ineffective or sometimes infeasible data dissemination [28]. Distributed machine learning algorithms, originally fuelled by the need to scale up learning algorithms in big data domains [29], [30], [31], [32] are designed to mitigate these shortcomings [33], [34] but heavily rely on data exchange [35], [36].

Ambient Intelligence often distributes data via sensors in the environment while device constraints (e.g. energy, storage) limit data mobility. Data can be fragmented horizontally (distribution of data instances) or vertically (distribution of feature values) [37], [38], [39] (cf. figure 2).

Many distributed learning algorithms share ideas from ensemble learning, where a set of different classifiers are trained on subsets of the data (populating different hypotheses h_i) [40]. Results are then combined according to the ensemble technique [39], [41], [42]. This procedure provably decreases the error with increasing number of classifiers and is more likely to meet constraints of constrained devices by dividing the data and problem complexity into smaller pieces. It is also scalable and respects data privacy due to distributed processing and data [43].

Other approaches comprise effective voting (evaluating statistical significance of classifier performance with paired t tests) [32] and consensus-based methods [39]. However, these are of low relevance in Ambient Intelligence environments with limited inter-device communication means.

Recently, Federated learning (FL) is gaining increased attention, which addresses both data separation and data privacy [44], [45]. In FL, a global model is trained by the individual devices with local data, so that the model is known to all devices while the data is not shared [46].

We propose Camouflage learning, which distributes the data in the same way as vertical federated learning, and in addition obfuscates the model for all devices and for the coordinator. It thereby addresses privacy requirements of sensitive data in Ambient Intelligence, such as medical records, behaviour patterns or identity [47], [48], [49].

Other proposals towards privacy preserving distributed learning [50], [51] comprise, for instance, homomorphic encryption [52], differential privacy [53], [54], [55], cyclic parameter or secret sharing [48], [56], using oblivious transfer [57], as well as multi-party computation [58]. These protocols, however, require additional processing or communication overhead.

Instead, for Camouflage learning we reduce the computation and communication load through backscattering physical layer computation offloading (here physical-layer superposition of weighted features) which simultaneously obscures data from prospective eavesdroppers. Camouflage learning provides differential privacy since nothing can be learned about the individual data provided from the superimposed aggregate. In addition, information on the model (i.e. features and weights) is distributed and not shared fully with any single device or even with the coordinator.

2.2 Efficient sensing, processing and communication

In Ambient Intelligence domains, constrained devices limit the energy budget, which in turn constrains the computational and communication capabilities of devices [59]. Hence, local data processing, sensing and communication must be energy-optimized [60], [61], [62], [63].

We suggest to employ chemical and organic sensors that feature energy consumption in the order of few μW [64], [65], [66]. Some examples of low-power sensors are the MMA865xFC accelerometer (19.8μW), the MPL3115A2

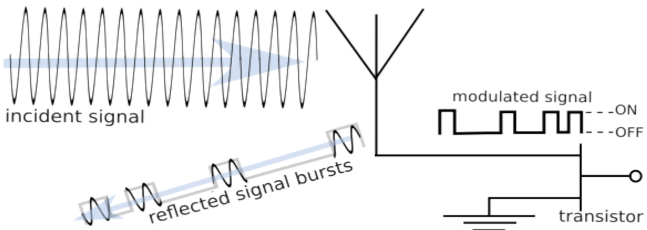


Fig. 4. Conceptional principle of backscattering burst sequences

pressure sensor (26.4μW), the PCT2202UK temperature sensor (4.6μW), the MAG3110 magnetometer (56.8μW)[1], or the 3.3μW vibration sensor [67], [68].

Furthermore, ultra-low power microprocessors are advisable for the use in Ambient Intelligence domains [69], [70]. Battery-free operation can then be achieved via power harvesting [71]. The interested reader is referred to the good overviews available on the topic, for instance, [17], [72], [73], [74] Our approach can be combined with energy harvesting and any sensor or microprocessor as only feature extraction, multiplication with a weight value and evaluation of a stochastic process are required [75].

The communication load can be reduced via algorithmic solutions, such as compressed sensing [76], which can recover sparse signals from far fewer samples than what is predicted by the Nyquist-Shannon sampling theorem [77], [78]. However, it requires complex data preparation, which contradicts the processing and energy constraints in Ambient Intelligence domain. Alternatively, low-power transmission protocols help to reduce the energy consumption through communication [21]. As depicted in figure 3, traditional, even low-power schemes consume significant energy [79], [80], [81], [82]. This involves also LoRa, a Long Range chirp spread spectrum modulation technique [83] that is receiving increased attention recently for its improved efficiency in long range communication [84].

On the other end of the spectrum are backscatter type systems that do not employ an own oscillator and signal generator but instead modulate their signals onto a reflected environmental signal (cf. figure 4) [85], [86]. Due to the absence of a dedicated signal generator and oscillator, the communication cost can be significantly reduced [87]. This mechanism can offer long-range communication by means of frequency synthesizers [79], [88] and oscillators [89] and various authors have considered backscatter communication for ambient Intelligence environments [90], [91]. We utilize a stripped-down (no frequency synthesizer or oscillator) prototype backscatter device that minimizes device complexity, cost and power consumption while compromising the transmission range [89], [92], [93]. We show that the backscatter prototype is feasible for indoor scenarios with a communication range of up to 6 meters. We exploit physical layer probabilistic collaboration for data transmission, to overcome device synchronization overhead and to trade computation cost for communication cost.

[1] Low Power Sensing Whitepaper: http://cache.freescale.com/files/sensors/doc/white_paper/LOWPOWERSENSWP.pdf

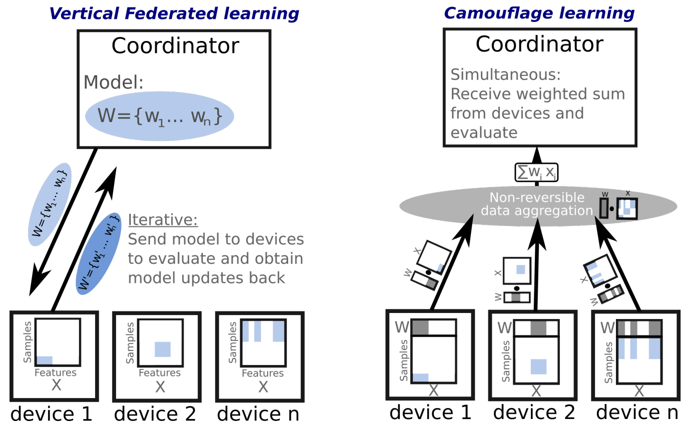


Fig. 5. Concepts of vertical federated learning and Camouflage learning.

2.3 Low overhead device collaboration

In constrained device communication, collision and scheduling of transmissions is a central concern [94], [95], [96]. For ambient backscatter-type communication (in contrast to e.g. RFID [97]), this is of particular concern, as devices are not synchronized by a strong signal to read out the tags [98]. This is addressed by collision-resistant protocols for simultaneous transmission which scale to large number of simultaneously transmitting nodes [22], [99], [100].

We exploit superposition of simultaneously transmitted sequences for data aggregation and to obscure data from distributed transmitters to realize Camouflage learning.

Function computation via superposition of wireless signals was first suggested in [101]. Goldenbaum *et al.* [102], [103], [104], [105] calculated the arithmetic mean, the geometric mean, polynomials and other functions at the time of transmission with suitable pre- and post-processing. This approach requires accurate time synchronization and to control transmit signal power, which is challenging for constrained devices and backscatter communication.

We propose probabilistic collaboration to achieve physical-layer aggregation for non-synchronized distributed devices [106]. In particular, we utilize Poisson-distributed burst sequences to compute the sum of the weighted feature inputs $\sum_{i=1}^{n} w_i x_i$ during simultaneous transmission. Synchronisation with respect to phase, transmit symbols or transmission power is not required.

Related work using physical layer computation offloading has addressed anomaly detection [107], activity recognition [108] and distributed machine learning [109]. From these, [107], [109] are dependent on tight device synchronization as it uses the protocol from [102]. Similar to [108], they use computation-offloading as a helper, but do not spread the model across distributed devices.

Instead, we implement both the training and the inference process on the through function computation on the wireless communication channel and utilize probabilistic collaboration to obscure data for camouflage learning.

3 Camouflage Learning

We propose Camouflage learning, a distributed machine learning scheme that obfuscates part of the model to all participating devices. In Camouflage learning, neither the

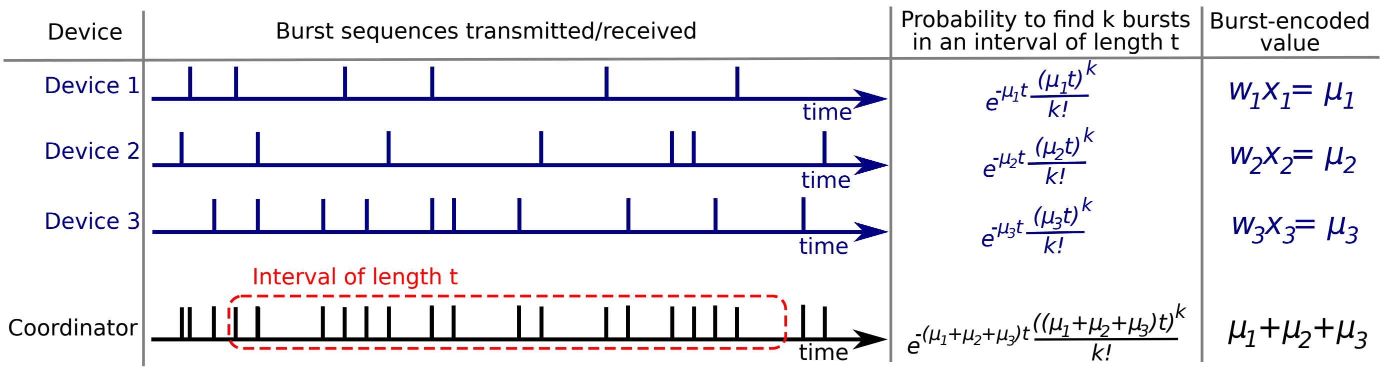


Fig. 6. Computation offloading and aggregation of the weighted feature values $w_i x_i$ during simultaneous superimposed transmission. Weighted feature values are transmitted as the mean $w_i x_i = \mu_i$ of a Poisson-distributed burst sequence. The coordinator estimates the mean $\sum_i \mu_i$ of the convoluted Poisson-distributed sequence to obtain an estimate on $\sum_i w_i x_i$.

coordinator nor any of the participating devices is at any time aware of the complete model. Figure 5 compares vertical Federated learning [34] with Camouflage learning. While in vertical Federated learning devices compute and share local model updates (model known to all devices), in Camouflage learning, the coordinator computes a single model inference from the received aggregated information $\sum_{i=1}^{n} w_i x_i$ for a particular set of inputs $\mathbf{x}$ (section 3.1). For $n > 2$, it is infeasible for the coordinator or any individual device $d_j, j \neq i$ to extract x_i or w_i from $\sum_{i=1}^{n} w_i x_i$. Learning is achieved iteratively between the coordinator and devices, alternatingly sharing the loss and their feature updates (section 3.2).

We demonstrate Camouflage learning for distributed linear regression [110]. Other approaches, that utilize aggregation over weighted feature values (e.g. neural networks, support vector machines), can be realized analogously [111].

Consider an instrumented environment with distributed backscatter-equipped sensors $d_i, i = 1, ..., n$, such as temperature, humidity, light, audio, etc. A device d_i extracts features x_i and holds and updates the weight w_i. (without loss of generality, we assume that a single device extracts a single.) Through non-reversible data aggregation via probabilistic collaboration and physical layer computation offloading, devices share $\sum_i w_i x_i = \mathbf{w}^T \mathbf{x}$ with the coordinator to compute $h(x) = \frac{1}{1+e^{w^T x}} + c$. Learning is achieved through an iterative protocol to minimize the loss $l(\mathbf{w}^T \mathbf{x})$.

3.1 Model inference via probabilistic collaboration

Model inference is achieved via probabilistic collaboration through physical layer computation offloading as depicted exemplarily in figure 6. In particular, when triggered by the coordinator, devices d_i read out their feature value x_i, multiply it with the weight w_i and transmit $\mu_i = w_i x_i$ by modulating signal bursts onto a reflected incident signal. The values μ_i are encoded as a burst sequence that follows a Poisson-distribution with mean μ_i. In particular, for a time duration of T, device d_i repeatedly transmits a burst (ON) with probability $e^{-\mu_i t} \frac{(\mu_i t)^k}{tk!}$ and no burst (OFF) else. Superimposing n such sequences during physical layer computation offloading, again yields a Poisson distributed burst sequence with mean $\mathbf{M} = \sum_{i=1}^{n} \mu_i$ [112] (cf. figure 6). Note that, for $T >> t$, the aggregation is independent of device synchronization in phase, amplitude and time, since bursts are counted irrespective of the signal phase and amplitude and since at any time, device d_i transmits a burst with the same probability $e^{-\mu_i t} \frac{(\mu_i t)^k}{tk!}$, which is only conditioned on $w_i x_i$.

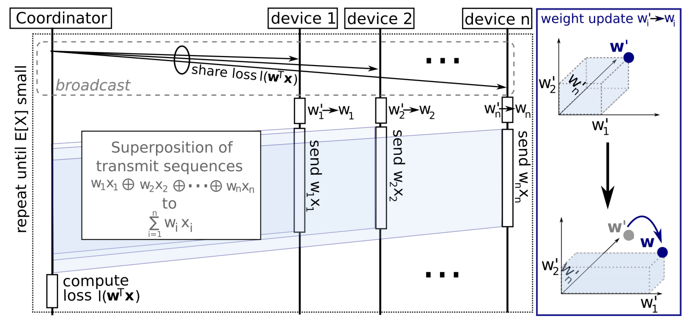


Fig. 7. To train the Camouflage learner, distributed weights are iteratively optimized via gradient descent.

The coordinator decodes a received burst sequence by counting the number of bursts in a pre-defined interval of length t and thereby estimating the mean $\mathbf{M} = \sum_{i=1}^{n} w_i x_i$ of the distribution encoded in the superimposed signal sequence [106]. From this non-reversibly aggregated weighted sum of the individual features, the coordinator then computes the model inference as $h(x) = \frac{1}{1+e^{w^T x}} + c$.

While burst collisions can not be avoided in the scheme, their probability, and hence the accuracy in the estimation of the distribution at the receiver can be controlled repeating the estimation multiple times (for $T >> t$) and by proper choice of k, t and T [106].

3.2 Training distributed weights

For training, we implement a gradient descent variant [110]. Guided by information on the loss shared by the coordinator, distributed devices d_i update their respective weight values w_i following a local random search protocol until convergence is reached (cf. figure 7) [111]. Let's first assume that devices are equipped with a common Rx interface

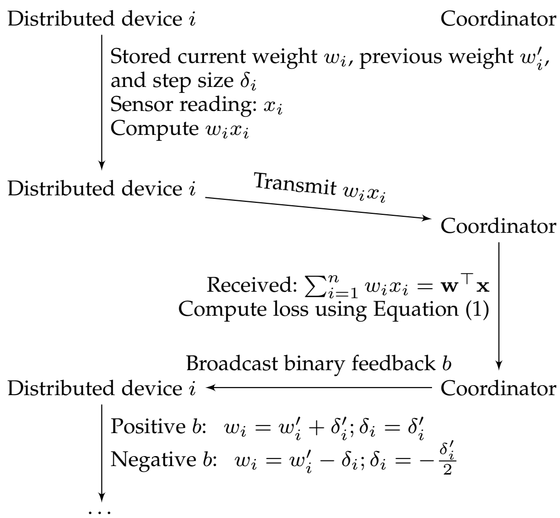


Fig. 8. Update of device d_i weight w_i based on binary input b. The process is repeated until convergence.

receive $l(\mathbf{w}^T\mathbf{x})$ from the coordinator with

$$\begin{aligned} l(\mathbf{w}^T\mathbf{x}) &= -\log\left(L(\mathbf{w}^T\mathbf{x})\right) \\ &= -y\log\left(h(\mathbf{x})\right) \\ &\qquad +(1-y)\log\left(1-h(\mathbf{x})\right) \end{aligned} \tag{1}$$

Since devices d_i are not aware of $w_j, j \neq i$, they are not capable of computing a standard gradient descent update as

$$w_i = w'_i + \lambda \cdot \frac{\partial}{\partial w'_i} l(\mathbf{w'}^T\mathbf{x}). \tag{2}$$

Instead, each device d_i will conduct a local random search on the 1-dimensional space of w_i as

$$w_i = \begin{cases} w'_i + \delta'_i; \quad \delta_i \leftarrow \delta'_i & \text{if } l(\mathbf{w}^T\mathbf{x}) \text{ improved} \\ w'_i - \delta'_i; \; \delta_i \leftarrow -\frac{\delta'_i}{2} & \text{else} \end{cases} \tag{3}$$

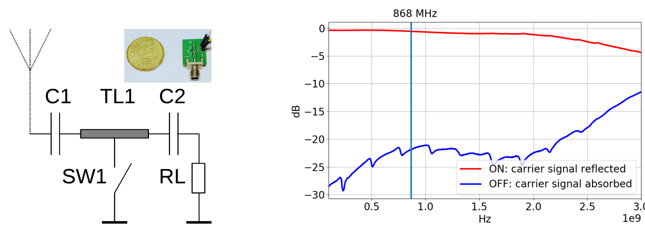
With w'_i and δ'_i we denote the old/previous value of w_i and δ_i, before updating the weights.

Since in Ambient Intelligence domains, devices are expected to be constrained, we implement the feedback from the coordinator as either a broadcast signal transmission ($l(\mathbf{w}^T\mathbf{x})$ improved) or no signal (($l(\mathbf{w}^T\mathbf{x})$ worse). We can read out this information from the backscatter interface by monitoring the voltage change on the interface. Also for the binary feedback, the optimization of the weights follows the update mechanism in equation (3) (cf. figure 8).

4 A PROTOTYPE BACKSCATTER DEVICE

We designed prototype backscatter devices to implement Camouflage learning in an Ambient intelligent environment (cf. figure 9a). For data modulation, we absorb (OFF) or reflect (ON) the signal. The device consists of only five components and can be connected to a microcontroller to guide the modulation onto the reflected signal via the switch (SW1). We used a 50 Ω (Ohm) transmission line, terminated with a power detector circuit matched to 50 Ω[2].

[2]For simple backscattering, only a resistor is needed. The power detector allows communication back from the coordinator (voltage-based data reception for binary feedback)



(a) Schematic (b) Reflected power up to 3GHz

Fig. 9. Schematic for our backscatter prototype. The components are a 50 Ω transmission line (TL1), a power detector circuit matched to 50 Ω and which serves as a terminating resistor (RL), a switch (SW1) and two DC-blocking capacitors (C1, C2).

The signal propagates the transmission line and is absorbed by the power detector circuit (non-reflecting OFF-state). The reflecting ON-state is realized using a current-controlled switch to reflect the signal back.

4.1 Equipment cost

We purchased the components to produce the backscatter devices from Digikey [3]. The highest cost is that of an SMA connector jack WM17359-ND with 3.92 EUR (approximately 4.39 USD). For the final device design with a fixed operating frequency patch antenna printed on the back of the board, this cost can be discarded. The diode (SW1) Infineon Technologies BAR8802VH6327XTSA1 costs less than 0.1 EUR (approximately 0.12 USD). This low device cost is essential to realize smart environments with massive deployment of backscatter-equipped sensors.

For comparison, active system including RF switch (2.5 USD), ultra-low power oscillator (1.8 USD) and a multiplexer (2.6 USD) will raise the cost significantly [89].

4.2 Input return loss

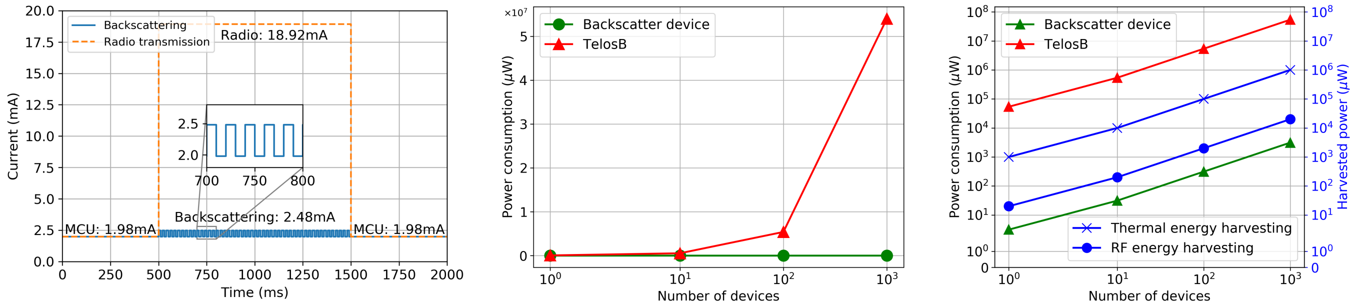
We measured the characteristics of the modulator with a network analyser. In particular, we are interested in the input return loss, which tells how much the back-scattered signal is attenuated in non-reflecting and reflecting states. Figure 9b depicts the average of the measurements for ten of or our backscatter devices. Observe that the received power difference between ON-state and OFF-state is about 20dB up to approximately 2GHz. In addition, the received power for the ON-state is close to 0dB. Due to the regulation of radio frequencies and our available licenses, we select the frequency of 868MHz in our experiments in section 5.

4.3 Power consumption

For signal reflection and modulation, the backscatter device uses 0.5 mA continuously over 10ms. [4]. In addition, the microcontroller operating the voltage-controlled switch demands 1.98mA MCU. For operation, our prototype consumes 0.9mW with an 1.8V operating voltage and 2.5mW

[3]https://www.digikey.com/

[4]The power consumption can be further reduced by using RF switches such as Analog Devices HMC190BMS8 [89]. For instance, using 5 V to control the switch, the current consumption would drop to 1μA, which is small enough to supply with an RF energy harvester [114]



(a) Current consumption during transmission: backscatter prototype vs. CC2420 [113]
(b) Estimated power consumption of our prototype and TelosB [113] for transmission
(c) Power consumption vs. energy harvesting: TelosB and backscatter prototype [114]

Fig. 10. Performance comparison: TelosB [113] vs. backscatter prototype, and estimated amount of energy harvested from ambient sources [114]

INDOOR [115]	OUTDOOR [116]
Environmental information in an office over several days. Modalities: temperature, humidity, CO_2 level, and light intensity. The ground-truth was acquired using a surveillance camera. The target of this dataset is to detect occupancy of the office: whether there are people inside the office or not.	Scattered sensors over $900 \times 300\text{m}^2$, separated by at least 20-40m. Modalities: acoustic (microphone), seismic (geophone), and infrared (polarized IR sensor). The data describes vehicles from two classes: tracked and wheeled.

Fig. 11. Datasets used to feed continuous streams of data to devices in our experiments

with 5 V. For comparison, PLoRa power consumption is 2.591 mW (250× smaller than LoRa) [117].

Figure 10a compares a CC2420 802.15.4 radio transceiver to our backscatter prototype, both operated by a 8Mhz 16-bit TI MSP430 micro-controller [118] (1.98mA MCU). To transmit a packet (0dB), the CC2420 draws a current of 18.92mA-1.98mA= 16.94 mA in 1012ms [119]. We chose the CC2420 and MSP430 for their use by the TelosB [113], [120], which draws less current than, e.g. the LoRaBug [121].

Figure 10b and figure 10c show the power advantage of our prototype[5]. Using -5dBm Tx power, TelosB consumes 54mW (transmit), 60mW (listen), 61mW (receive), and 4.8mW (compute). For fair comparison, we assumed the same backscatter compute power consumption of 4.8mW.

We estimate the average power of communication $P_{MSG} = \frac{E_{MSG}}{T_{MSG}}$ as the amount required to send a message E_{MSG} over the duration between consecutive messages T_{MSG} [122]. For $T_{MSG} = 1$, the average energy amount required to send a message is $0.003125mJ$ using our backscatter device, $0.0035mJ$ using PLoRa, and $4.17mJ$ using LoRa.

5 EXPERIMENTS

We study Camouflage learning and our hardware prototype with respect to transmission range, communication load, classification, training and environmental impacts.

5.1 Distributed model inference and training

We compare Camouflage learning to other distributed machine learning approaches using two datasets (cf. figure 11). These datasets were chosen for their relevance to Ambient Intelligence, diversity in size, number of features, and sensors [115], [116]. We assign one feature to each distributed device. For OUTDOOR [116], we randomly split 75% for training and 25% for testing while for INDOOR [115], we follow the authors approach to use six days for training and the remaining days for testing.

We compared Camouflage learning against a non-distributed logistic regression (using scikit-learn 0.20.1 [6]) and federated learning.

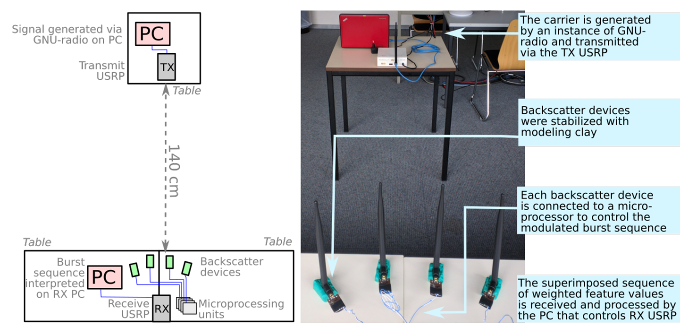


Fig. 12. Device installation for the case study

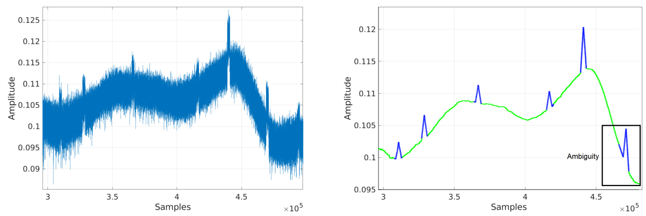
5.1.1 Probabilistic collaboration experiment

To test the burst recognition accuracy for Probabilistic collaboration through physical layer computation offloading, we utilized the *Indoor* dataset and employed four backscatter devices, one for each feature stream (light, temperature, humidity, and CO_2). To generate and read out the modulated signals reflected from the backscatter prototypes, two Ettus N200 USRPs (SBX daughterboards, 868MHz, 1MHz sampling rate) were used as Tx and Rx (cf. figure 12).

Devices modulated their weighted (see section 3.2) feature values ($w_i x_i$) periodically via Poisson-distributed burst sequences onto the reflected signals. The samples were averaged over non-overlapping 60 second feature windows, since each sensor had its own sampling rate. The burst

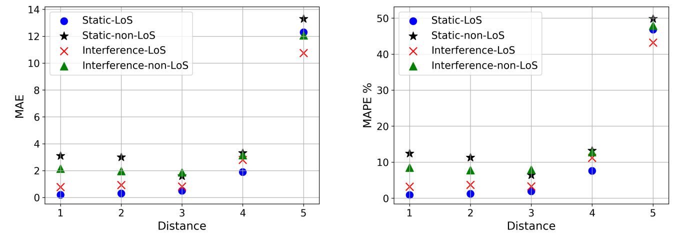
[5] Estimated according to $\frac{1}{2}CV^2F$ [93] with diode capacitance C, voltage V and frequency F)

[6] https://scikit-learn.org/stable/



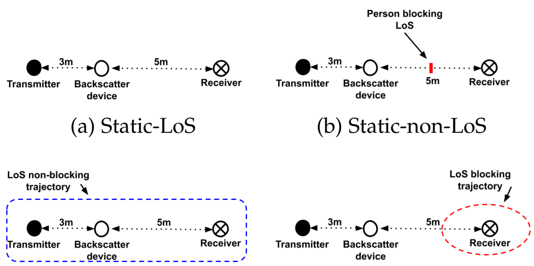
(a) Raw signal amplitude (b) Filtered signal

Fig. 13. Ambiguity of detected bursts when there is movement



(a) Mean Absolute Error (b) MAPE Error

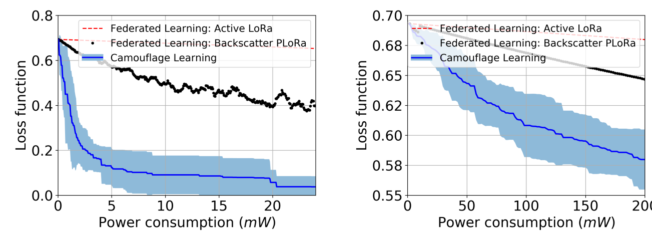
Fig. 15. Burst detection in various environmental conditions



(a) Static-LoS (b) Static-non-LoS

(c) Interference-LoS (d) Interference-non-LoS

Fig. 14. Layout of devices in the experiments on environmental variation



(a) INDOOR [115]: 4 features, 8143 training samples (b) OUTDOOR [116]: 100 features, 73896 training samples

Fig. 16. Power consumption: Camouflage vs. Federated learning

length was 10-20ms and for accurate estimation of the burst recognition accuracy, we maintained the transmission for 60 seconds. For burst detection, our instrumentation achieved a precision of 0.9 and a recall of 0.89. Overall, camouflage learning for the INDOOR dataset achieved an accuracy of 0.82 (F_1 score 0.82). For comparison, training logistic regression via gradient descent on a desktop computer (Intel Core i5 1.8GHz, 8GB RAM, with scikit-learn library version 0.20.1) achieved an accuracy of 0.94 (F_1 score 0.93).

5.1.2 Effect of changes in an environment

Human movement in the monitored area may affect the wireless channel and hence impact the burst detection accuracy [123]. For example, a person blocking the line-of-sight (LoS) between a backscatter device and the receiver (RX) or human movement may increase the noise floor and impair the correct counting of bursts at the receiver (cf. figure 13).

We investigated the impact of four types of human interference, (a) *Static-LoS*: No person in the room or people sitting still and not blocking the line-of-sight, (b) *Static-non-LoS*: A person blocks the line-of-sight between backscatter device and RX), (c) *Interference-LoS*: One person moves around in the room, not blocking the line-of-sight, and (d) *Interference-non-LoS*: One person moves around freely in the room, occasionally blocking the line-of-sight between a backscatter device and RX (figure 14).

In cases, we varied the distance between backscatter and Rx from 3m to 5m while modulating 50 distinct humidity samples x_i from the INDOOR dataset ($16.7 \leq x_i \leq 39.1$; $\sigma = 25.7$, std=5.5) through physical layer probabilistic collaboration. The burst detection Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) at the Rx is shown in figure 15. The MAE is at most 3.5 within 3m and higher when the signal is blocked or at larger distance. Possible improvements can be achieved by locating devices above human height and by template matching.

5.1.3 Model performance through distributed training

Figure 16a and figure 16b depict the convergence speed of the algorithms. The figures plot the loss along with the confidence interval (10 repetitions). Camouflage learning uses less power to optimize the weights of the logistic regression model. The prediction accuracyies achieved are competitive: INDOOR 0.92 (0.94), OUTDOOR 0.72 (0.78) (cf. figure 17 and figure 18).

The power consumption of our backscatter device is $0.003125mW$. For comparison, that of PLoRa [117] is $0.0035mW$, which implements frequency shifting for backscattering communication, while that of an active LoRa node is $4.17mW$ [117]. Based on these figures, we estimate the power utilized during training on two datasets [115] [116]

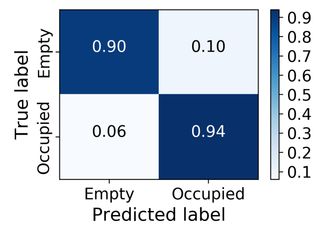
Finally, Camouflage learning also exchanges less data overall (figure 19). This is because federated learning requires active data transmission and reception of all devices.

5.2 Communication range

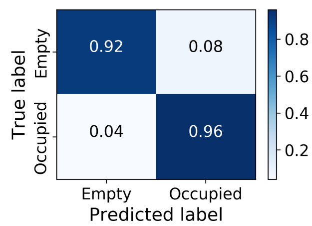
The communication range of ambient backscatter devices is severely limited since the reflected modulated signal is magnitudes lower than that of the original carrier signal [86]. In this section, we investigate the communication range of our ambient backscatter devices in real indoor environments and with respect to different antenna configurations.

5.2.1 Omnidirectional antennas

In our first setting with an early prototype version of our backscatter interface, we investigated the communication range utilizing an omnidirectional antenna (Ettus VERT900

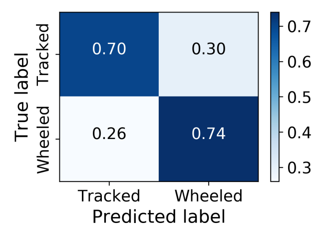


(a) Camouflage learning

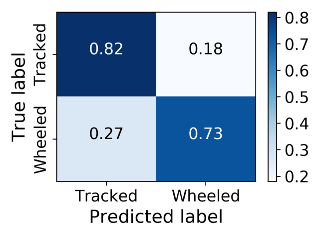


(b) Federated learning

Fig. 17. Confusion matrices for the INDOOR dataset [115]

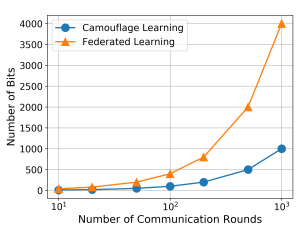


(a) Camouflage learning

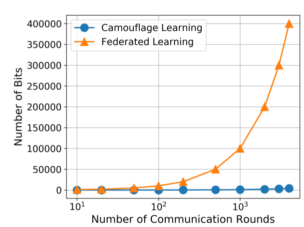


(b) Federated learning

Fig. 18. Confusion matrices for the OUTDOOR dataset [116]



(a) INDOOR dataset [115]



(b) OUTDOOR dataset [116]

Fig. 19. Communication load: Camouflage vs. Federated learning

824 to 960 MHz, 1710 to 1990 MHz Quad-band Cellular/PCS and ISM Band omnidirectional vertical antenna, at 3dBi gain). In this early prototype manufactured on fiber glass circuit board, we used a general purpose diode (1N4148), 470 nF / 50 V ceramic capacitors and a terminating resistor made of two parallel connected 100 Ohm resistors. The device was brought out in line-of-sight between Tx and Rx (Ettus N200 USRPs with SBX daughterboards using the same omnidirectional antenna, see figure 20). Gradually moving Tx and Rx farther away (1m to 1.5m; step size 0.1m), the received power at the backscatter device ranged from approximately 1.1mW to 486μW and after 1.4m the prototype ceased to detect the backscattered binary sequence.

We improved the prototype with superior components: BAR8802VH6327XTSA1 Infineon Technologies diode, 10 nF

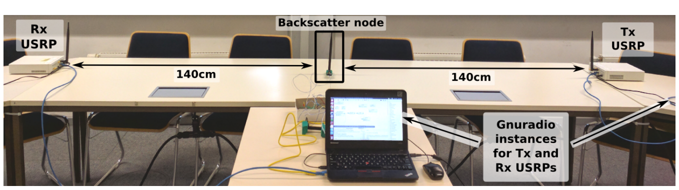
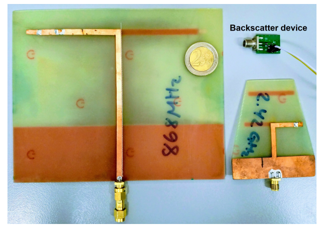
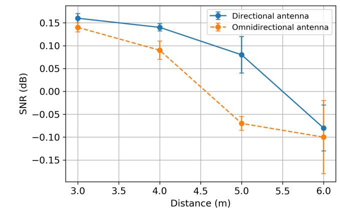


Fig. 20. Measuring the working distance of our first prototype



(a) Semi-directional antennas (868MHz and 2.42GHz) used



(b) Signal-to-noise ratio (SNR) with various distances

Fig. 21. Microstrip antennas (fiber glass board and copper layers, relative permittivity 4.5, maximum gain 4.7dBi) and their impact on the range

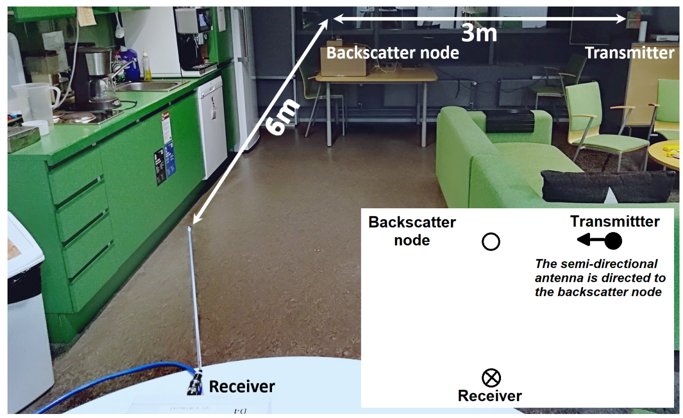


Fig. 22. Layout of our experiments on the operating distance

capacitors, a 49.9 Ohm resistor and directional antennas.

5.2.2 *Semi-directional antennas*

We used semi-directional antennas (figure 21a) to extend the range of the system. In a larger indoor space (figure 22) we placed Ettus N200 USRP devices (SBX daughterboards, 868MHz, 1MHz sample rate) at 3m (Tx) and 1-6m (Rx) from the backscatter prototype.

Measurements were conducted with both omnidirectional and directional-type Tx antennas and repeated 10 times for each distance and antenna type (figure 21b). The signal strength at the prototype with omnidirectional antenna was approximately 121μW. The signal was well received up to 5m, which is sufficient for many indoor environments. To further extend the range, we suggest the use of switching frequency control [124] or frequency synthesizers [79], [89].

6 DISCUSSION

We discuss further aspects of camouflage learning below.

6.1 Backscatter design

While our design does not limit to the operating frequency, the limiting factor is the quality of components used to manufacture the device. With ideal components, the termination resistor would be perfectly matched to the transmission line and the reflection coefficient in non-reflecting state would be 0 while with an ideal switch, all power would be reflected back for a reflection coefficient of -1.

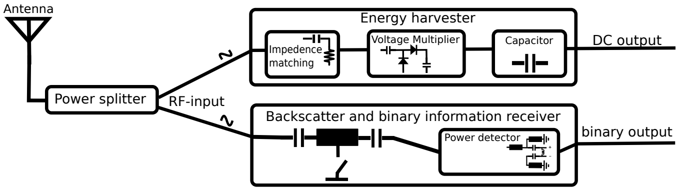


Fig. 23. Schematic of a generic energy harvesting device. Power splitter for simultaneous energy harvesting and information reception.

The switching diode used has a parasitic capacitance of 0.28 pF (OFF) and 2 Ω forward resistance (ON), so that the return loss in ON-state is 0.70 dB. Correspondingly, the reactance of the parasitic capacitor in parallel with the terminating resistor gives a return loss of 28.4 dB in the OFF-state.

A diode requires a constant current to keep it conducting (in this case 0.5 mA). Traditionally, a switching diode is biased backwards when not conducting by applying a negative voltage, thus minimizing the off-state capacitance. For improved results, we suggest, a voltage- instead of current-controlled element, such as a field effect transistor.

The circuit board material used in our experiments is also not optimized for RF applications and the performance therefore starts to degrade above 2GHz frequency.

6.2 Energy harvesting for battery-free operation

For long-term deployments, a maintenance-free operation is desired [125]. The power consumption of the TI CC2650 controlled backscatter device is lower than the power that can be harvested from solar and thermoelectrics [114]. The amount that can be collected from RF sources with 4cm^2 antenna (transmit power 4 W and distance 15 m) and thermal 1cm^2 piezoelectric material is 20μW and 1mW, respectively [114]. Using improved components can further reduce the power consumption of the backscatter prototype.

Figure 23 depicts a generic architecture for energy harvesting devices. In particular, the device is able to exploit the received power both for energy harvesting and, simultaneously, for information reception. We propose to employ power-splitting, as this achieves better tradeoffs between information rate and amount of RF energy transferred when compared to simpler time-slotted schemes [126], [127].

Experiments on the amount of harvested RF energy from ambient RF signals indicate that about 2μW of energy can be harvested from isotropic 2W RF transmitters (such as, for instance, WiFi) in about 25m distance [128], [129] and at about $0.5 - 1.5$V [130], [131]. For comparison, using digital TV signals, even an energy harvesting rate from over 60μW in typical distances of about 4km has been reported in [130]. This enables the operation of the aforementioned low-power or power-less (zero-power) environmental sensing devices.

6.3 Choice of antenna

For a production-level system, we propose to print a patch antenna, which is cheap to manufacture, on the back of the circuit board. Such antenna will need a rectangular space of $\frac{1}{4}$ to $\frac{1}{2}$ of wavelength λ. For instance, a backscatter system with a patch antenna in the 2GHz range could have dimensions smaller than $4\text{cm}\times 4\text{cm}$. Usually, antennas are matched to 50Ω, as all cables and connectors are also 50Ω. The natural impedance of the patch antenna is higher though, for instance, 100Ω. In this case, all circuitry should be matched to the same impedance as the antenna. This minimizes the return loss in ON-state as the ratio of the diode's forward resistance and the impedance of the antenna is bigger.

6.4 Privacy

With our distributed approach, the model is by design not shared but instead distributed among participating devices. Learning the model in our scheme means to reverse-engineer it from the model prediction, or to conduct advanced signal analysis and processing while inside the environment, both of which constitutes a significant effort [49].

Since the model is distributed and not known completely to any individual device, it is harder to steal and thereby to learn properties of the environment or its inhabitants [132]. It is also more difficult for any device, including the coordinator to learn of the feature values, since only the weighted sum is disclosed, which further contributes to improved privacy. Summarizing, we believe that Camouflage learning improves privacy in instrumented environments.

6.5 Camouflage learning with other learners

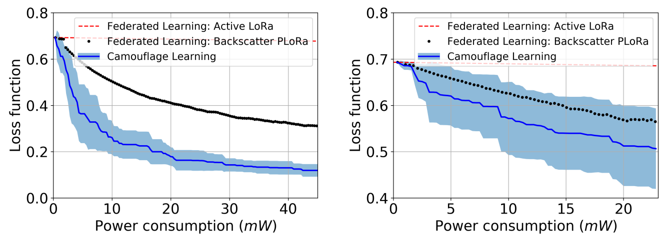
We have demonstrated camouflage learning via physical layer computation offloading with a logistic regression classifier. It is straightforward to extend the model for other learning approaches. For instance, aggregation of the weighted inputs in the first layer of a neural network, aggregation of the weighted features in the mathematical description of a support vector machine or also offloading the product of potential functions in conditional random fields by encoding the product terms as sum of logarithms.

6.6 Computational complexity

The computational complexity of the individual devices is comprised by a single multiplication ($w_i x_i$) and repeated random decisions on whether or not to switch to ON-state according to a Poisson distribution with mean $w_i x_i$. Both of these computations can be realized in hardware. At the receiver, for $10^{\eta-1} < W^T X \leq 10^{\eta}$, the complexity is $\mathcal{O}\left(\eta^{1.465} \cdot \log(\eta)\right)$ [133], where the term $\eta^{1.465}$ is according to 3-way Toom-Cook multiplication [134].

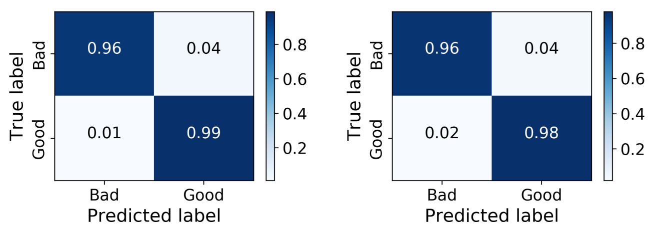
6.7 Application to arbitrary datasets

Camouflage learning can be applied to arbitrary datasets and applications are not restricted to Ambient Intelligence domains. To demonstrate this, we verified camouflage learning on two benchmarking datasets [135] [136]. We achieved classification performances for camouflage (federated) learning 0.98 (0.97) (INTRUSION DETECTION [135]: 494020 samples, 40 features) and 0.75 (0.80) (PHISHING [136]: 11055 samples, 30 features) as depicted in figure 25 and figure 26. Figure 27 shows that Camouflage learning requires strictly less data transmission in both datasets.



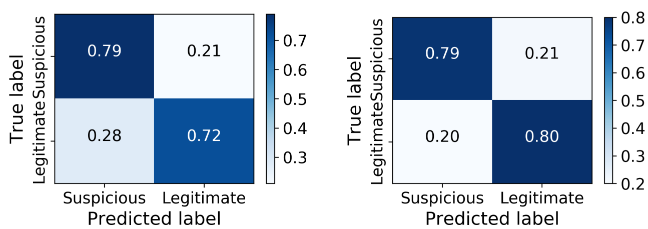
(a) INTRUSION [135] (b) PHISHING [136]

Fig. 24. Power consumption of Camouflage learning and non-distributed logistic regression (Active LoRa Node and PLoRa [117])



(a) Camouflage learning (b) Federated learning

Fig. 25. Confusion matrices for the INTRUSION dataset [135]



(a) Camouflage learning (b) Federated learning

Fig. 26. Confusion matrices for the PHISHING dataset [136]

7 CONCLUSION

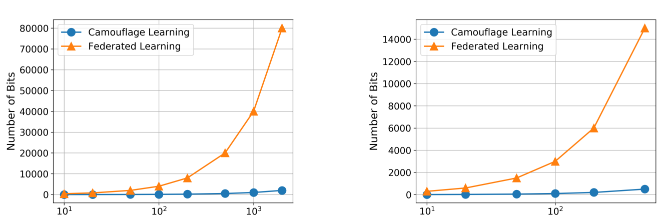
We have proposed Camouflage learning, a distributed machine learning technique for vertically-partitioned data collected by distributed sensing devices. Our approach achieves energy-less computation via physical-layer computation offloading, exploiting interference of backscattered signals for data aggregation. It thereby brings battery-free distributed learning and continuous operation in Ambient Intelligence environments into reach.

Each sensor-equipped device acquires and processes environmental stimuli and modulates the weighted feature values $w_i x_i$ as Poisson-distributed burst sequences onto a reflected electromagnetic signal. The coordinator estimates the weighted sum $\sum_i w_i x_i$ from the superimposed burst sequences to evaluate and guide the model optimization via binary feedback.

None of the devices nor the coordinator is at any time aware of the complete model. Camouflage learning advances the state-of-the-art with respect to (1) *Physical layer Computation offloading*, (2) obscuring the model via *total distribution*, (3) *Model training through distributed random search*, and (4) *Zero-synchronization requirement* thanks to probabilistic collaboration via superimposed Poisson-distributed burst sequences for weighted feature aggregation.

We extensively evaluated the scheme in comparison to traditional approaches with respect to power efficiency, prediction accuracy as well as various aspects and limitations of the prototype hardware.

Camouflage learning was evaluated using prototype backscatter devices deployed in indoor environments.



(a) INTRUSION [135] (b) PHISHING [136]

Fig. 27. Communication load of Camouflage and federated learning [39]

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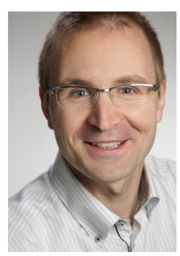

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