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Machine learning in distributed, federated and non-stationary environments - recent trends

Mirko Polato[1] and Barbara Hammer[2] and Frank-Michael Schleif[3]

1 - University of Turin, Department of Computer Science, Turin, Italy
2 - Bielefeld University, CITEC, Bielefeld, Germany
3 - Technical UAS Würzburg-Schweinfurt, Dept. of CS, Würzburg, Germany

Abstract. This tutorial provides an overview of machine learning methodologies applied in distributed, federated, and non-stationary environments. We focus on recent advancements and novel research contributions of the field. Key topics include data analysis and pattern recognition for non-stationary environments, model compression, federated learning algorithms, and privacy preservation. This tutorial aims to equip researchers and practitioners with insights into current challenges and innovative solutions in this dynamic field.

1 Introduction

Machine learning has evolved to accommodate the challenges posed by distributed and non-stationary environments, in particular to better address practical needs [1]. In these settings, data is often distributed across multiple locations, requiring methods that ensure privacy and adapt to changes over time. This paper provides a short comprehensive overview of the state-of-the-art techniques and applications in these domains. We target the setting of federated learning first as this constitutes one of the current key concepts to learn in distributed environments with different clients without an exchange of possibly private training data among those clients. This setup meets demands as occur in relevant application domains including self-driving cars, digital health, or smart manufacturing. Afterwards, we have a glimpse at two specific challenges which occur in distributed learning scenarios and beyond: how to deal with distributional shift which causes the necessity of client models to adapt to diverse and possibly non-stationary data distributions? How to provide models which provably obey privacy concerns as regards the observed training data?

2 Distributed and Federated Learning

Federated Learning (FL) is an innovative approach to train machine learning models on decentralized data, first introduced by researchers from Google in 2016 [2]. Unlike traditional centralized methods, FL enables multiple clients to collaboratively train a model while keeping their datasets local, thereby preserving data privacy and security.

Definition 1 (Federated Learning). *Consider a set of N clients, each with a private dataset relevant to a shared learning task. The objective is to train* *a global model M that minimizes the error on an objective function E in a distributed manner. The FL process typically involves the following steps:*

1. *Model Initialization: An initial model is distributed to all clients.*
2. *Local Training: Each client C_i updates the model M_i using its local dataset.*
3. *Model Aggregation: A central server aggregates the locally updated models M_i into a global model M, which is then redistributed to the clients.*

The decentralized approach of FL offers several advantages:

- *Privacy Preservation*: Data remains on local devices, aligning with regulations such as the GDPR[1].
- *Efficient Resource Utilization*: The method leverages the computational power of clients.
- *Access to Diverse and Heterogeneous Data and Information*: It enables learning from otherwise inaccessible and possibly heterogeneous data and information distributed across clients.

FL can be distinguished along different dimensions. A prominent categorization used in [3] refers to the split of users and features among clients and distinguishes *horizontal FL*, *vertical FL*, and *Federated Transfer Learning*. Here, horizontal FL refers to a distribution of data with overlapping features but different users among clients (e.g. different probes); vertical FL refers to a distribution of different features but the same users along clients (e.g. different sensors); FTL refers to a small overlap of both, features and users among clients.

An alternative categorization was suggested in [4] with four groups, which distinguishes FL techniques along the challenges and desired features: *Aggregation optimization*, *Heterogeneous federated learning*, *Secure federated learning*, *Fair federated learning*. Here, aggregation refers to the way in which the individual models learned by each client are summarized. Prominent approaches average along weights or feature, for example. Heterogeneous FL refers to the form of heterogeneity which can be dealt with by the specific FL approach, such as differences in the model type or the underlying data distribution considered among clients. Secure FL refers to strategies which guarantee a correct result in the light pf possibly malicious clients; these might attack the results by targeting its functionality (e.g., backdoor attacks or model poisoning), or its privacy (e.g., using gradient information to uncover individual data from the communication schemes). Fair FL aims at a global model which takes into account the interest of all clients involved in the learning scheme in a suitable way, i.e., it is fair to all clients. This notion aligns with trends in processing large-scale community data and complies with ethical AI guidelines[2].

[1] `https://gdprinfo.eu/`

[2] `https://digital-strategy.ec.europa.eu/en/library/ethics-guidelines-trustworthy-ai`

Other surveys on FL distinguish further relevant aspects [5] such as the applicable individual machine learning models, the involved privacy mechanisms, or the used communication architecture, among others. FL has been used in various applications [4] and is implemented in different frameworks, like *FLOWER* [6], *PySyft* [7], *FATE* [8], *TensorFlowFederated* [9], or *OpenFL* [10].

Recent advancements

While FL enhances privacy and reduces data transfer costs, it also introduces unique challenges. As recent deep learning is often based on fine-tuning of foundational deep learning models rather than training from scratch, the suitability of *federated learning strategies for optimization of foundational models* constitutes an active area of research [11]. Some challenges which occur in this context concern communication and computation efficiency as it is unclear which parts of a model (including prompt engineering for LLMs) to adapt when finetuning a deep architecture. Federated model pruning strategies, for example, can significantly increase the efficiency of FL, for example [12].

Another line of research deals with the *enhancement of FL technologies by components of explainability*, as is required for trustworthy machine learning models [13]. Recent approaches target efficient FL for natively explainable models [14]. Ongoing work demonstrates a possibly limited explainability for privacy preserving FL approaches [15].

When dealing with non-stationary data, FL faces a number of additional, dedicated challenges, in particular *Data Distribution Shifts and Drifts.* Sine each client device may have its own distinct data distribution, these individual distributions can change over time. This non-stationarity makes it difficult for the global model to generalize across all devices since the model may encounter drastically different data patterns during each training round. For distributional shift, work on transfer learning could be used, but the resource constraints on the client make this a challenging task [16]. Another promising approach is Personalized FL where clients are allowed to "customize" the global model in order to better capture the peculiarities of their own dataset [17].

Unlike shift, concept drift occurs when the statistical properties of the target variable, which the model is predicting, change over time. In a federated setting, this drift might be different across various clients, leading to models that become outdated quickly if not continuously adapted. Addressing these challenges requires developing adaptive algorithms capable of learning from changing data distributions, ensuring robust model aggregation techniques, and leveraging techniques like continual learning [18], statistical control measures [19] and transfer learning [1, 20] to maintain model performance over time.

Marfoq recently formalized the challenge of *federated learning for separate data streams* and provided a theoretical analysis thereof [21]. Currently, there has been a notable advancement in the field, such that Federated Learning has been extended to handling of non-independent and identically distributed (non-i.i.d) data (potentially still in static, batch processing) [22]. For a more general overview we refer to [23, 4].

Contributions in the special session

The work in [24] focus on sampling strategies from federated streaming data, addressing challenges in data heterogeneity and model accuracy. The session also includes a novel Personalized Federated Learning approach [25] based on Prototype Learning that highly reduce the communication cost while having a performance close to the state-of-the-art.

3 Non-Stationary and Dynamic Environments

Non-stationary environments present significant challenges for machine learning models, as they require adapting to changes in the underlying data distribution over time. In FL, this may affect individual clients, but it constitutes a more general challenge for global models in real environments, as one may not any longer assume that data are independent and identical distributed (i.i.d.). Formally, learning takes place based on an underlying family of distributions D_t, where t refers to the current time point, and $D_{t_1} \neq D_{t_2}$ might hold for at lest two given time points $t_1 \neq t_2$, i.e., concept drift occurs. Drift might manifest itself in a change of the input distribution, the posterior distribution, or any representation of features (see e.g. [26, 27] for a detailed recent discussion). Hence the current model might become invalid either because there does not exist a model fitting both D_{t_1} and D_{t_2}, or because the variability of D_{t_2} cannot easily be predicted based on D_{t_1}. Key challenges of learning in non-stationary environments are:

- **Concept Drift:** Concept drift refers to change of the underlying distribution D_t with t. Drift can be gradual or abrupt and it poses a significant challenge in maintaining model accuracy. Challenges include concept drift detection, i.e., localization of drift in time, localization of concept drift in space [26], and explanation of concept drift [28].

- **Real-time Adaptation:** Various incremental learning technologies have been proposed which are capable of model adaptation in the presence of concept drift, ensuring that models remain relevant and effective [29]. Thereby, models must be able to update continuously or periodically to incorporate new data patterns based on limited memory. Further, as non-stationary environments often require real-time or near-real-time adaptation to changes, efficient incremental approaches which might be implemented on the edge become particularly interesting [30]. While many approaches rely on supervised information, unsupervised learning models, which estimate label values from the context, become of increasing importance in autonomous learning scenarios [31].

- **Data Scarcity and Imbalance:** In dynamic environments, data scarcity and imbalance can exacerbate the challenge of learning from non-stationary data. Certain data patterns may become infrequent or rare, making it difficult for models to learn or generalize effectively [32].

- **Model Evaluation and Validation:** Traditional evaluation methods may not be suitable for non-stationary environments, as they often rely on static test datasets that do not reflect the dynamic nature of the environment. In supervised incremental learning, evaluation is often based on continuous evaluation strategies such as the interleaved train-test-error [29]. Yet evaluating a suitable model plasticity and stability is challenging, and alternative evaluation schemes have based on data representation, for example, have been investigated [33].

In this context, various techniques such as online learning, ensemble methods, and adaptive algorithms play a crucial role in managing non-stationary data effectively. Leveraging transfer learning and continual learning approaches can help models adapt to non-stationary environments by transferring knowledge from previous tasks or experiences. These techniques enable models to retain useful information while adapting to new data [34, 35, 36, 37].

Contributions in the special session

Feature learning is a crucial part in dynamic environment with particular challenges due to the non-stationarity of the underlying data distributions. The session includes two papers addressing this field. In [38] feature learning for time series is considered in detail and a new type of discriminative features is suggested. Adapting to concept drift is crucial for maintaining model performance. In the work of [39] the fine-structure of drifting features is explored, providing insights into feature stability and adaptability.

4 Data Privacy and Security

Ensuring data privacy and security is paramount in federated learning environments and beyond. Mathematically founded privacy concepts and secure aggregation are key techniques used to protect sensitive information. Three popular techniques are commonly employed in FL techniques, often in combination, to achieve this goal:

1. **Homomorphic Encryption** allows computations on encrypted data without decryption. An example approach is additive homomorphism [40].

2. **Differential Privacy** [41], limits information leakage during learning by ensuring that small changes in the training dataset do not significantly affect the model's output. This technique prevents attackers from extracting precise individual data by introducing controlled noise or using complex compression techniques [42].

3. **Secure Model Aggregation** is the most prevalent technique, where the global model is trained by aggregating model parameters from all clients, thus preventing the disclosure of original data. A notable deep learning approach in this domain is described in [43].

One may also use multi-task learning, where local models are trained individually and subsequently combined [44]. Additionally, blockchain technologies can securely aggregate local model parameters [45]. A more recent overview and proposal is given in [46].

Contributions in the special session

Schubert and Villmann investigate in [47] vector quantization methods to enhance privacy in federated settings, offering promising results for secure model training.

5 Applications of Machine Learning in Federated Settings

Various applications benefit from federated learning approaches, including healthcare, finance, and environmental monitoring. Some overview papers can be found here in [48, 49].

Contributions in the special session

Case Study: Federated Learning for Earth Observation The authors of [50] demonstrate the application of federated learning in semi-supervised environments for earth observation data, highlighting the potential for scalable and privacy-preserving analytics.

Motion Classification via Electromyography Also in the medical domain dynamic and non-stationary data are an important source of information. In [51] a few-shot learning approach for motion classification using electromyography is presented, showcasing the versatility of federated learning in diverse domains.

6 Conclusion and Future Directions

Machine learning in distributed, federated, and non-stationary environments continues to evolve, driven by the need for privacy-preserving and adaptive models. In particular we may see the convergence of different subfields to better address application constraints. Future research should focus on improving model robustness, communication efficiency, and privacy guarantees which are particular challenging in non-stationary environments and with ressource constraint devices.

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