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# A Path Towards Fair and Equitable AI Advancing Bias Mitigation in Federated Learning

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► **To cite this version:**

Ferraguig Lynda, A Benoit, Faiza Loukil, Mickaël Bettinelli, Christophe Lin-Kwong-Chon. A Path Towards Fair and Equitable AI Advancing Bias Mitigation in Federated Learning. The IEEE International Symposium on Women in Services Computing (WISC 2023), Jul 2023, Chicago, United States. , 10.13140/RG.2.2.23701.29921 . hal-04158784

**HAL Id: hal-04158784**

**<https://hal.science/hal-04158784v1>**

Submitted on 11 Jul 2023

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### Introduction

- Machine learning is nowadays used in practically every domain to analyze data and guide the decision-making process.
- With the advent of big data, machine learning has evolved towards decentralized solutions to be more efficient.
- As technology advances, several regulations have been introduced with respect to data privacy, such as the GDPR.
- To address the security and privacy issues surrounding data, Google introduced Federated Learning (FL) in 2016 [McMahan et al., 2016].
- FL is a promising approach for privacy preserving ML but also brings various challenges, notably bias and fairness in AI models.

### Federated Learning An Overview

**Federated Learning Definition.** (FL) is a machine-learning setting where multiple entities (clients) collaborate in solving a machine-learning problem, under the coordination of a central server or service provider. Each client's raw data is stored locally and not exchanged or transferred; instead, focused updates intended for immediate aggregation are used to achieve the learning objective. [Kairouz et al., 2021]

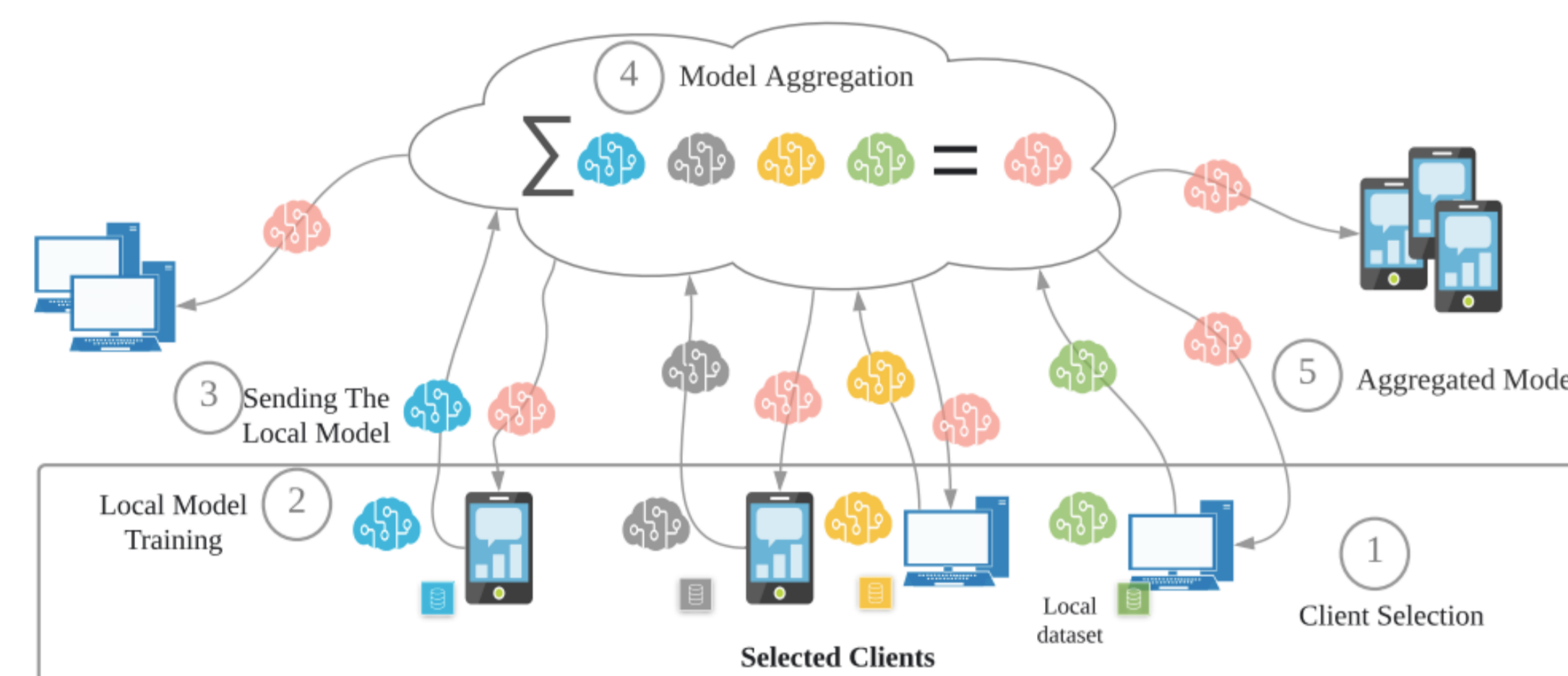


Figure 1. Federated Learning Steps [Ferraguig et al., 2021]

#### FL Workflow:

- (1) Client Selection by the server
- (2) Local Training at each Client's level
- (3) Sending Focused Updates by each Client
- (4) Model Aggregation by the server
- (5) Clients receiving an aggregated global model

### Fairness And Bias in Machine Learning

- Fairness, Sensitive Attributes.** The technical definitions of fairness in machine learning are based on the concept of sensitive attribute, also known as a protected attribute, which are characteristics that divide the population into groups based on certain common traits, such as gender, religion, etc. A machine learning model is considered unfair if it systematically exhibits biases that result in unjust treatment or disparate impact towards certain individuals or groups [Mehrabi et al., 2021].
- Bias.** is the inclination of a model to favor or discriminate against an individual or group in a manner considered unfair [Mehrabi et al., 2021].

### Sources And Impact Of Bias

Bias in machine learning can stem from various sources [Lambrecht, 2018] such as:

- Historical data reflecting past biases.
- Unintentional or intentional human biases in data collection and annotation
- Measurement biases during data collection.
- Representation bias caused by inadequate or underrepresented training data.

**Negative Impact Of Bias** Machine learning may learn how to be racist, sexist, and discriminatory [Mehrabi et al., 2021].



Figure 2. Impact of Bias In ML

### Bias Mitigation Techniques in Classical ML

- Pre-processing.** involve modifying the training data by applying techniques, such as data augmentation, data balancing, etc., to address bias before training the model. [Calders et al., 2009]
- In-processing.** focus on adjusting the learning algorithm to reduce bias during the training process [Kamishima et al., 2012].
- Post-processing.** involve applying fairness-aware algorithms to modify the predictions generated by the trained model to ensure fairness [Louppe et al., 2017].

### Fairness And Bias in Federated Learning

Why Is It Harder To Alleviate Bias In FL? [Chang and Shokri, 2023]

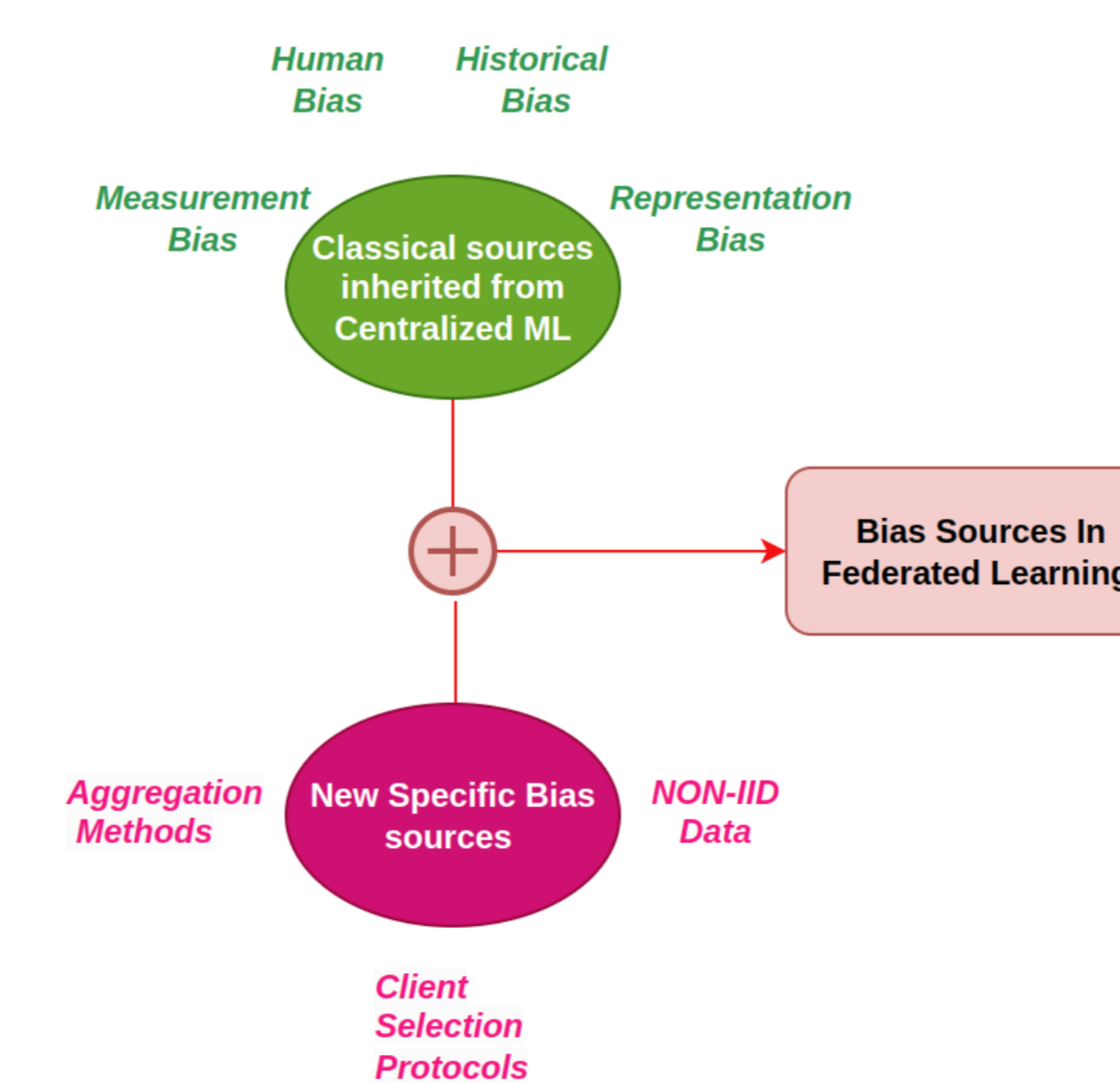


Figure 3. Source of Bias In FL

### Bias Mitigation In Federated Learning

#### 1. Existing Works

Paper	Main Findings
<i>Mitigating Bias in Federated Learning</i> (Abay et al., 2020)	-Explores causes of bias in Federated Learning (FL). -Test classical bias mitigation techniques in FL. -Proposes bias mitigation methods, and demonstrates their effectiveness in addressing data heterogeneity and ensuring fairness without compromising data privacy.
<i>Towards Bias Mitigation in Federated Learning</i> (Djebrouni et al., 2022)	-Characterize the impact of Federated Learning (FL) settings on bias. -Propose novel FL selection and aggregation methods for bias mitigation, without compromising privacy.
<i>Bias Propagation in Federated Learning</i> (Hongyan Chang et al., 2023)	-Bias in Federated Learning exceeds that of centralized training on the combined dataset. -Biased parties inadvertently encode their bias in a small number of model parameters, gradually increasing the model's reliance on sensitive attributes. -Auditing group fairness in Federated Learning is crucial, and robust learning algorithms are needed to mitigate bias propagation.
<i>Mitigating Group Bias in Federated Learning</i> (Ganghua Wang et al., 2023)	-Investigates the relationship between local and global model fairness in Federated Learning. -It recognizes the issue of group fairness and the limitations of centralized learning methods -The study proposes locally fair training to mitigate bias at the client level. -The researchers establish that global model fairness can be obtained using summary statistics from local clients.

#### 2. Promising Approaches

**Clustered Federated Learning (CFL).** addresses suboptimal results in FL due to diverging data distributions by grouping clients based on similar data and leveraging geometric properties for joint training. [Sattler et al., 2020, Duan et al., 2021]

**Personalized Federated Learning (PFL).** the training process is customized for each client based on their preferences. This helps overcome the problem of using a single model that may not work well with different types of data. As a result, performance is improved, and the model is better aligned with each client's specific goals. [Deng et al., 2020]

### Ongoing Work

- Propose a novel clustering method (CFL) to identify under and over-represented demographic populations.
- Propose innovative bias mitigation techniques that leverage Clustered Federated Learning (CFL) and Personalized Federated Learning (PFL) while considering FL privacy constraints.
- Evaluate the proposed approaches using real-world datasets to assess their effectiveness.

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