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Bias mitigation for collaborative & ethical learning on dynamic data

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Problem Statement

- Data growth drives the proliferation of machine learning and distributed machine learning.
- Federated learning (FL) addresses data privacy concerns but worsens bias in models.
- Bias refers to unfairness in model decisions, and privacy constraints in FL hinder traditional bias mitigation approaches.
- FL exacerbates bias, and classical mitigation techniques are not suitable due to privacy constraints.

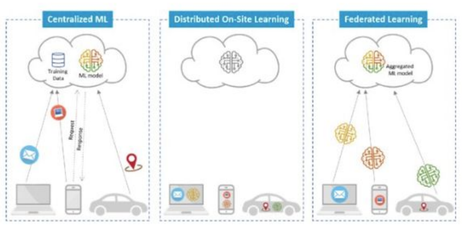
Goal

- Detect similar populations in federated learning (FL).
- Propose population-specific bias detection and correction solutions.
- Build personalized models for each population to improve generalization.
- Account for FL constraints: decentralized nature, non-IID data, dynamic and privacy.

DML

Evolution of DML architectures

- Classic DML involves grouping data together and training a distributed ML model, but may not consider data confidentiality or new regulations.
- On-site DML trains pre-trained models on data kept at the client's location, but performance may suffer due to clients not benefiting from each other's learned models.
- Federated Learning enables multiple clients to train the same ML model without sharing data, ensuring privacy and security while improving performance.

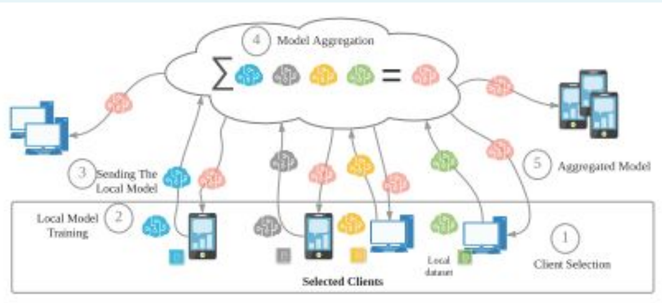


Centralized vs Distributed On-Site vs Federated Learning Architectures [1]

Federated Learning

FL an overview

- FL was proposed by Google in 2016 to address the challenge of training models on distributed data without compromising data privacy. [2]
- FL is a type of Distributed Machine Learning (DML) approach that emphasizes data confidentiality.
- FL allows clients to participate in model training without sharing data by training the model locally and sending only updates to a central server.



Federated Learning steps [3]

Fairness in Distributed Machine Learning

Why care about bias in distributed machine learning?

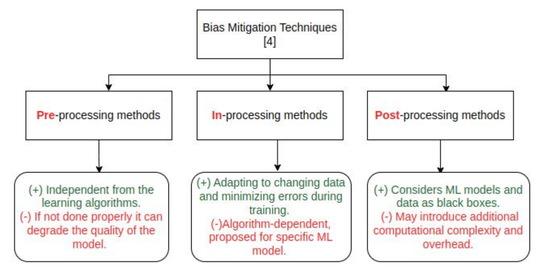
Definitions

- Fairness: Algorithm output should not disadvantage protected groups.[4]
- Bias: Systematic error leading to incorrect or unfair outcomes. [5]
- Sensitive attribute: Protected characteristic used to define subgroups for fairness analysis.[5]

Impact of bias on society [4]

Biased ML is sexist, racist and sends people wrongly to jail.

Mitigating Bias in DML systems



Bias correction techniques

Fairness in DML vs Fairness in FL [6]

ML paradigm Comparison criteria	Classical Machine Learning	Federated Learning
Data	-Full Access to data -Homogeneous dataset -Centralized in one location	-Data remains local -Non-IDD data -Distributed among clients
Source of Bias	- Historical Bias - Human Bias - Measurement Bias - Representation Bias	Classical one + : - Data heterogeneity -Aggregation -Client selection
Applicable Bias mitigation techniques	All Techniques are directly applicable	Need to be adjusted to fit FL constraints

Ongoing Work

- Clustering in federated learning to detect similar subpopulations
- Propose novel bias mitigation techniques that takes into account FL constraints
- Evaluate the proposed approaches on real world datasets

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