Flagging Hate Speech and Cyber-Bullying in Private Chats

Using distributed machine learning and federated learning techniques to preserve privacy when learning from personal data

Aditya Srivastava (CSCI 6502-001)
Harsh Gupta (CSCI 6502-001)

Problem Space

- Hate speech and cyber-bullying are significant problems in online interactions
- Most methods of policing objectionable online content only work on open and public data
  - Vetting by human moderators
  - Automated moderation tools

How to moderate private interactions between users without leaking their data or violating their privacy?

Proposed Work

Use federated learning for **privacy preserved** machine learning

- Send model to clients instead of fetching data from clients
- Does not require users to share their data
- Distributed **edge computing** for model training
- Learn from **large amounts of data**
- Use **MapReduce** to parallelize model aggregation

Prior Work

- Federated learning first introduced in 2017 by McMahan et al. [1]
- ML paradigm has since been **applied to many different domains**;
  - **Healthcare** (eg. personal IoT devices) [2]
  - **Mobile computing** (eg. autocorrect, next word prediction) [3]
  - **Finance** (eg. automated credit scoring) [4]
- Work on **productionizing FL at scale** has been undertaken by Google and Microsoft [5, 6]

Data

- Text classification problem
  - **Input:** English text
  - **Output:** Binary class (objectionable or not)
- Combine multiple datasets for testing

Dataset	Offensive	Inoffensive	Sample Size
Hate Speech Dataset [2]	599	2399	2998
Cyberbullying dataset [3]	57581	390552	448133
ConvAbuse [4]	758	2515	3283
Hate Speech and Offensive Language [5]	20620	4163	24783
Total After Removing Duplicates	**49683**	**213165**	**262848**

Data (Continued)

- Splits created
  - Full Model
    - ***Train-Eval-Test Ratio:*** 75 : 15 : 15
    - ***Samples:*** 183,993 : 39,427 : 39,428
  - Federated Clients
    - ***Identical and Independently Distributed (IID)***
    - ***Train:*** (# Total training samples)/(# Clients)
    - ***Eval and Test:*** No change
- Stress testing: 7.8 million sentences from Wikipedia.[12]

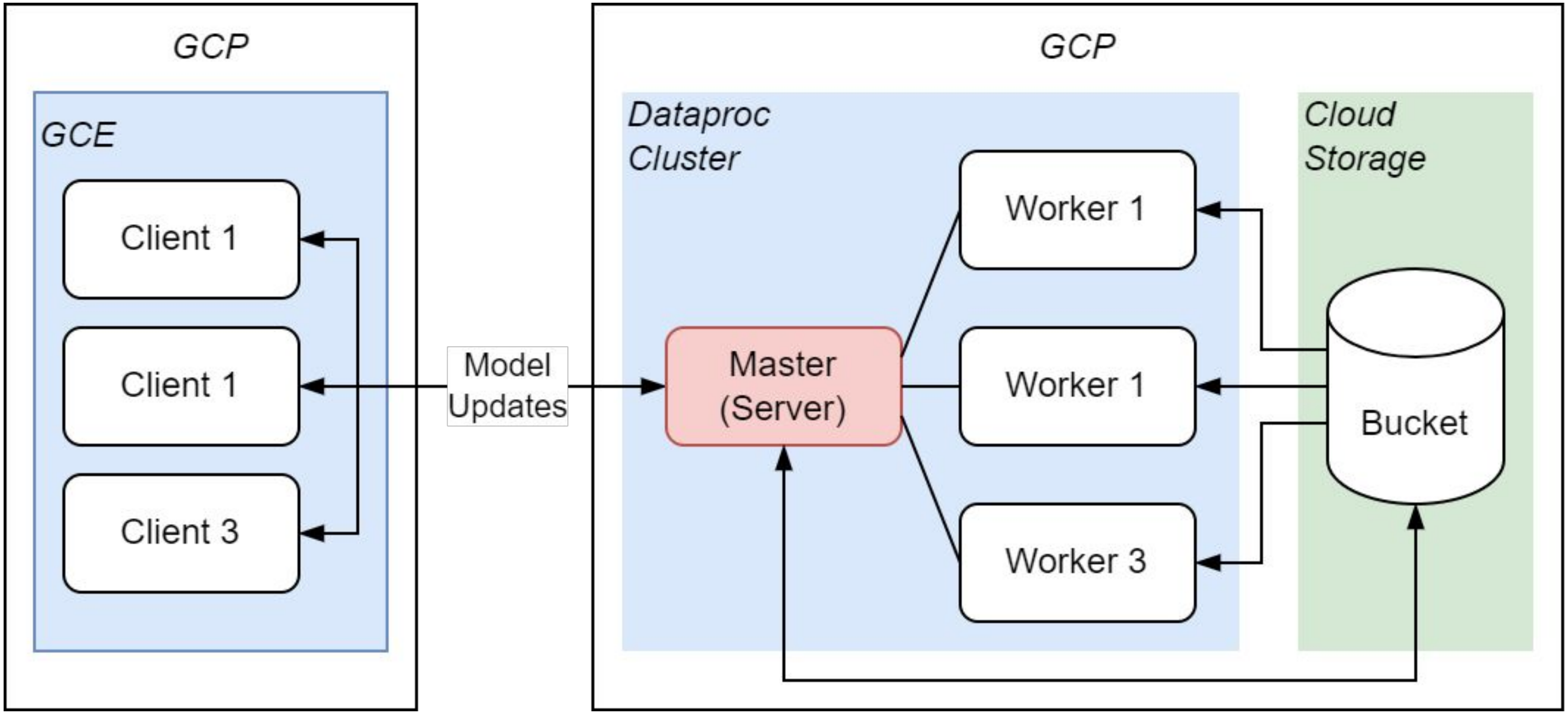
Infrastructure

- **Google Cloud Platform (GCP)**
  - Server
    - ***Dataproc Cluster*** *with* ***Google Compute Engine (GCE) instances***
      - Master node with **TPU**
    - ***Spark backend*** *for* ***MapReduce*** *operations*
  - Clients
    - ***GCE instances*** *with* ***GPUs***
- **Google Colab** for ML development and testing

Tools

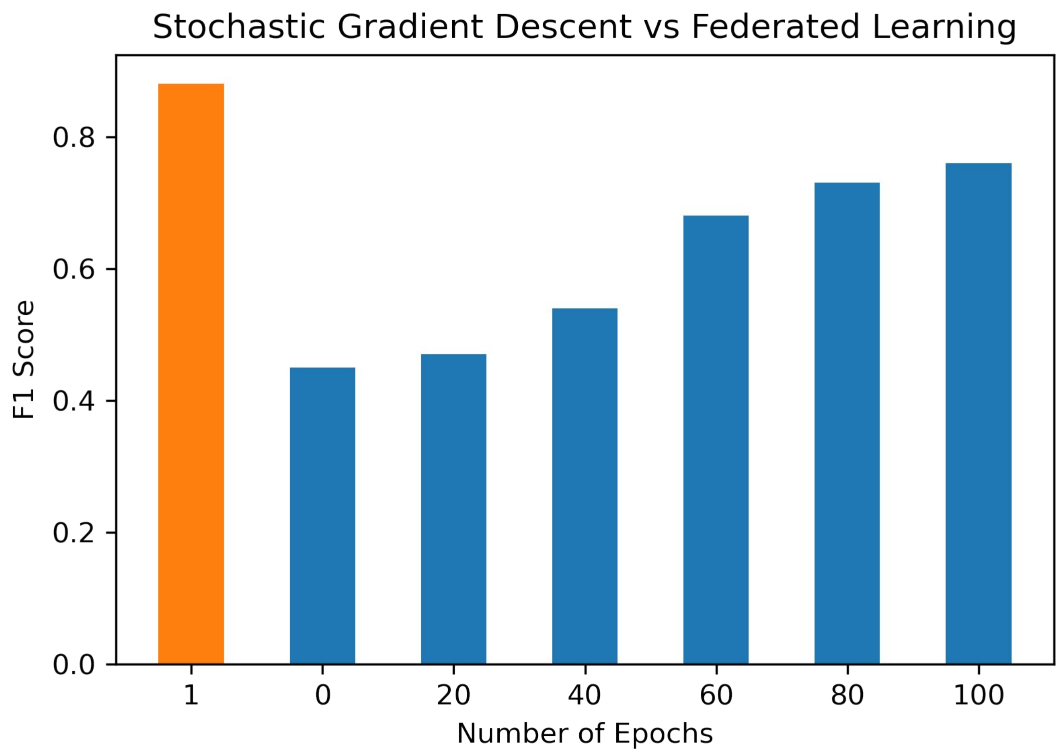
- **Linux OS**
- **Python**
  - **Flask** server and client applications
  - **Google Cloud APIs**
  - **Pytorch** for Machine Learning
  - 🤗 **HuggingFace** for pretrained language models
  - **PySpark** for MapReduce functionality

Architecture



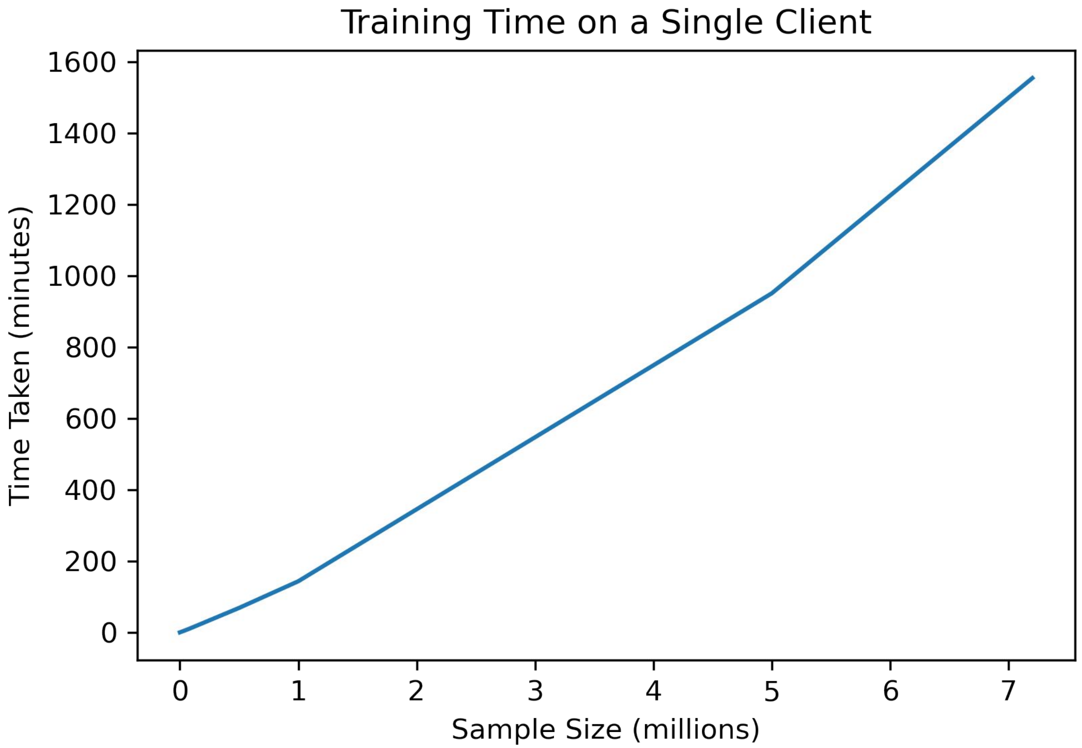
Evaluations

SGD vs Federated Averaging



- Training performed on **16 clients**
- **Best: 0.88** F1-score for SGD compared to **0.76** for FL

Impact of Data Size on Training

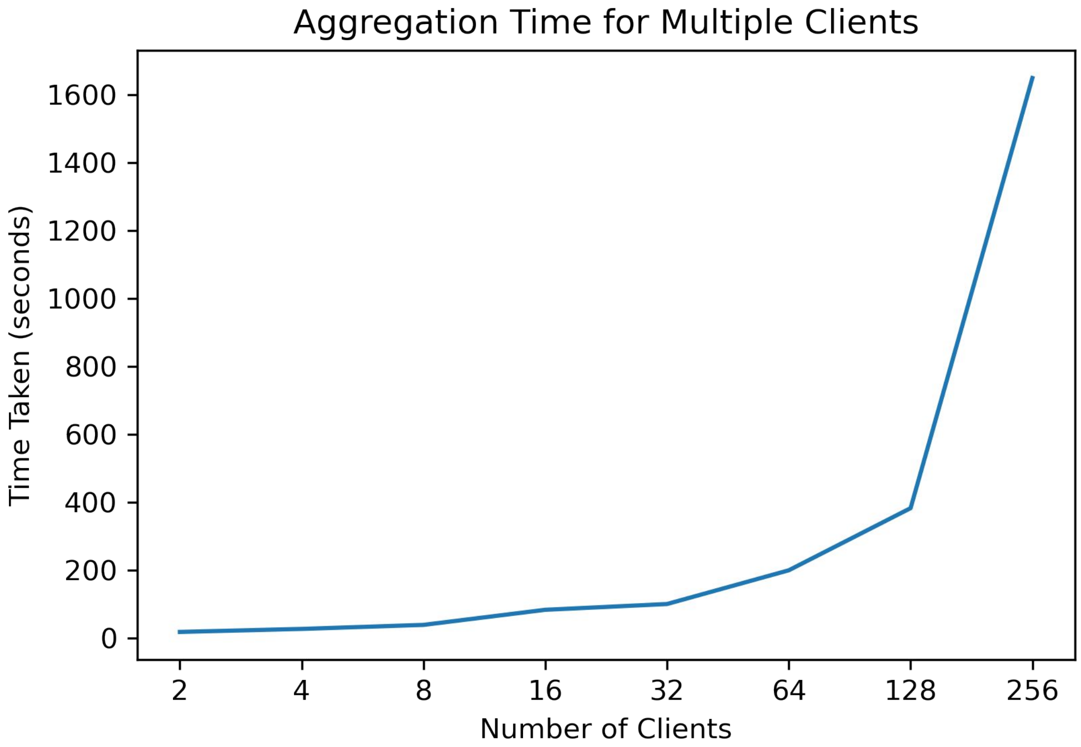


- Approximately linear curve
- Model loading time adds minimum overhead

Impact of #Clients on Training

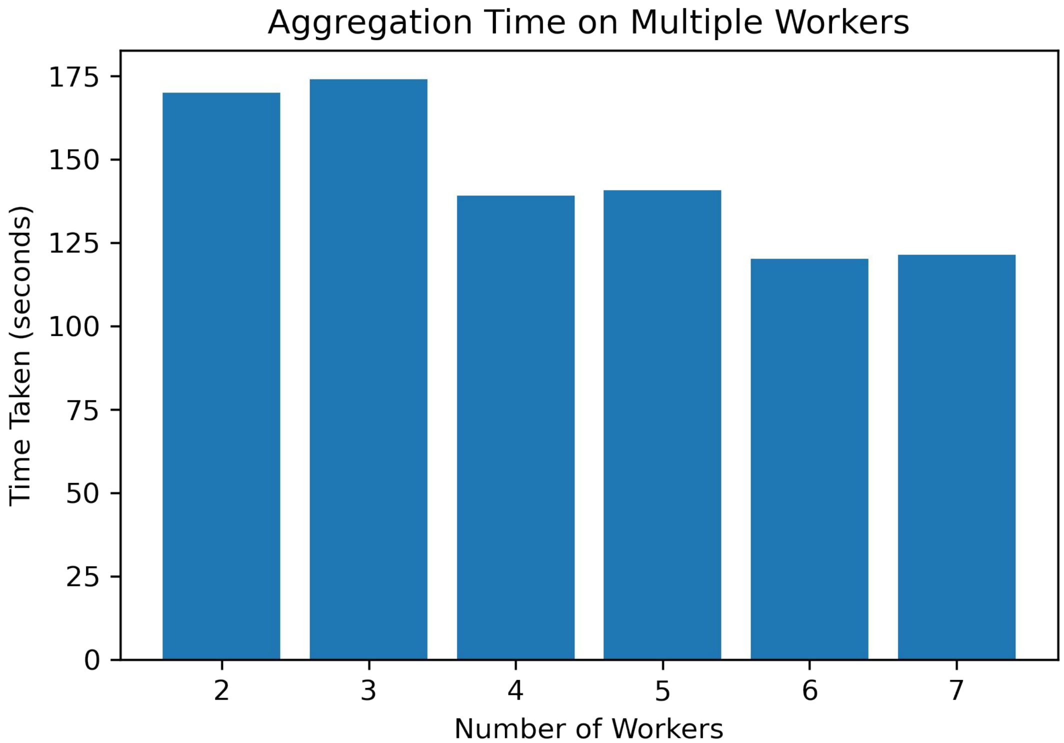
- #Samples remain constant as #Clients increase
- Exponential decrease as data is split between the clients

Impact of #Clients on Model Agg.



- Sharp rise in training time as #Clients increase
- Storage and Memory IO may take increasingly longer time

Impact of #Workers on Model Agg.



- Aggregation time decreases as the #Workers increase
- Odd #Workers do not contribute significantly more

Other Statistics

- **Average latency:** 28.215 ms (b/w server and client)
- **Average throughput:** 1360 samples/second (calculated over 5M samples, 16 clients, 4 workers)

Key Learnings

- FL Pros
  - High throughput (can handle more data and faster)
  - Data privacy
- FL Cons
  - Infrastructure expenses (compute, storage, etc)
  - High latency (transmitting models to clients and back)
  - Model Averaging < Gradient Descent

Challenges and Bottlenecks

- **Challenges**
  - Limited compute ($$$) - Colab and GCP
  - Synchronising model versions on the client and server
  - Models have a large memory footprint
  - Needs GPUs/TPUs for efficient training and evaluation
- **Bottlenecks**
  - Limited number of workers for MapReduce operations
  - Storage IO
  - Data transmission between server and clients

Up Next…

- Evaluating the pipeline on Non-IID data
- Evaluating weighted averaging
- Performing model evaluations using MapReduce routines

References

1. McMahan et al., *Communication-Efficient Learning of Deep Networks from Decentralized Data* (link)
2. Yuan et al., *A Federated Learning Framework for Healthcare IoT Devices* (link)
3. Hard et al., *Federated Learning for Mobile Keyboard Prediction* (link)
4. OpenMined, *Federated Learning for Credit Scoring* (link)
5. Google, *Towards Federated Learning at Scale: System Design* (link)
6. Microsoft Research, *FLUTE: A Scalable, Extensible Framework for High-Performance Federated Learning Simulations* (link)
7. Shane Cooke, *Labelled Hate Speech Dataset* (link)
8. Saurabh Shahane, *Cyberbullying Dataset* (link)
9. Curry et al., *ConvAbuse: Data, Analysis, and Benchmarks for Nuanced Abuse Detection in Conversational AI* (link)
10. Davidson et al., *Automated Hate Speech Detection and the Problem of Offensive Language* (link)
11. Andrii Samoshyn, *Hate Speech and Offensive Language Dataset* (link)
12. Wikipedia Dataset (link)