EPI RQ4 Research Update: Privacy Preserving Distributed Machine Learning

Saba Amiri

s.amiri@uva.nl

VINVERSITEIT VAN AMSTERDAM VOI VAN AMSTERDAM

Supervisor: Adam Belloum, Advisor: Eric Nalisnick

Promoters: Sander Klous, Leon Gommans

Multiscale Networked Systems Group

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Recap



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- Differentially private compressive federated learning
 - Simple federated learning setup
 - > Add differential privacy through compression mechanism necessary due to constrained communication channel
- Impact of non-i.i.d distribution on the performance of machine learning models
 - Different federated learning fusion schemes
 - Different non-i.i.d data distribution schemes
 - Impact of differential privacy
- Differentially private synthetic data generation
 - Distributed datasets
 - Privacy preserving
 - Non-i.i.d data distribution among nodes
 - Skewed/imbalanced dataset
- Modeling tail behavior of long-tailed distribution in generative models
 - > Synthetic data generation probabilistic machine learning models
 - > Verify their ability to capture the tail behavior of different data distributions, especially when the tail is long
 - The long tail as will be shown at the end of this presentation can be masked during the privacy preserving distributed machine learning process
- Distributed learning pipeline
 - Research on using Vantage6^[1] as the distributed machine learning infrastructure (as opposed to more generic solutions, e.g. managing the distributed pipeline through use of Pytorch distributed)



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- Impact of non-i.i.d distribution on the performance of machine learning models
 - > Paper submitted to IJCAI 2022 this month
 - Work in progress to extend the results (ETA: March 2022)
 - Next phase already planned (ETA: July 2022)
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 - Work in progress to extend the results
 - > Next phase already planned for summer
- Differentially private synthetic data generation
 - > Ablation study finished (Planning on submitting results, ETA: March 2022)
 - New model already beating SOTA benchmarks
 - > Early results on semantic integrity improvements (ETA: March 2022)
- > Modeling tail behavior of long-tailed distribution in generative models
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- Modeling tail behavior of long-tailed distribution in generative models
 - > Early results in, clear improvements observed on artificial data
 - Working on formalizing the method, extend results (ETA: June 2022)
- Distributed learning pipeline
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 - Working on formalizing the method, extend results
- Distributed learning pipeline
 - Finished, will be submitted to a FL workshop (ETA: August 2022)





Thank you!

My direct collaborators in chronological order

- Serge van Haag (AI)
- Boris Egelie (AI)
- Tidi Stamatiou (AI)
- Carlijn Nijhuis (Computer Science)
- Mike Schouw (Computer Science)
- Jetske Beks (Computer Science)
- Willemijn Beks (Computer Science)
- Yu Wang (Computer Science)
- Simon Tokloth (Data Science)

