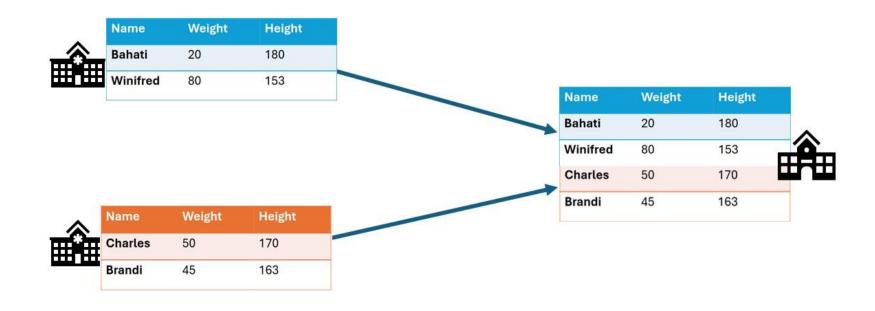


Introduction to Privacy Enhancing Technology



Classic analysis: Collect the data in one place

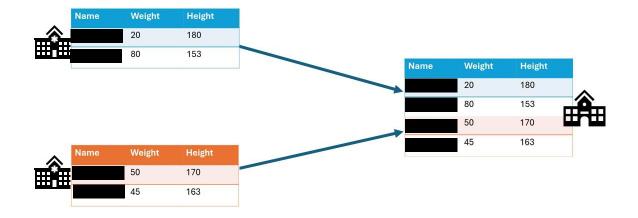






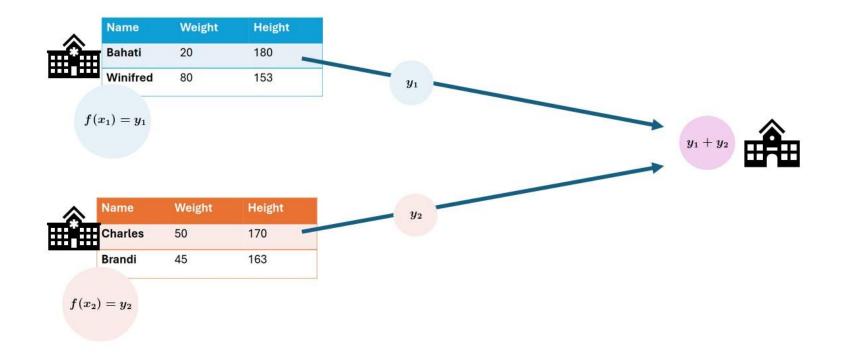
Data anonymization: Remove sensitive fields





Federated data analysis: Send analysis to the source, then aggregate

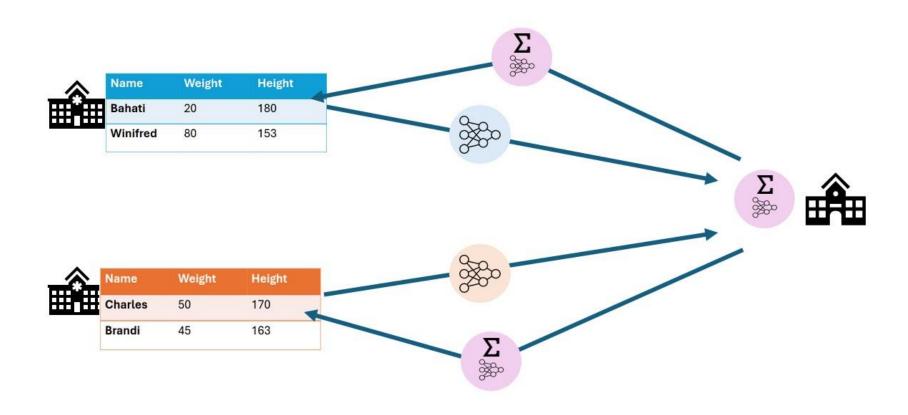






Federated learning: Train models locally, then aggregate



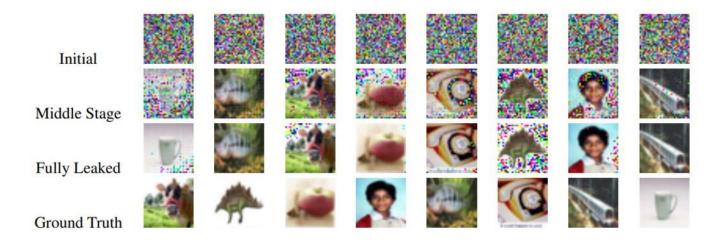




Federated learning and analysis can still leak data!



Gradient leakage

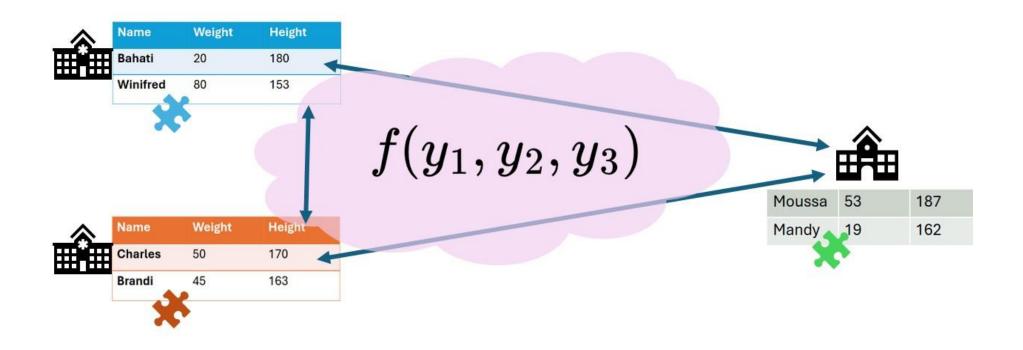


Zhu, Ligeng, Zhijian Liu, and Song Han. "Deep leakage from gradients." Advances in neural information processing systems 32 (2019).



Secure multiparty computation: Send around encrypted puzzle pieces







Secret sharing: an example

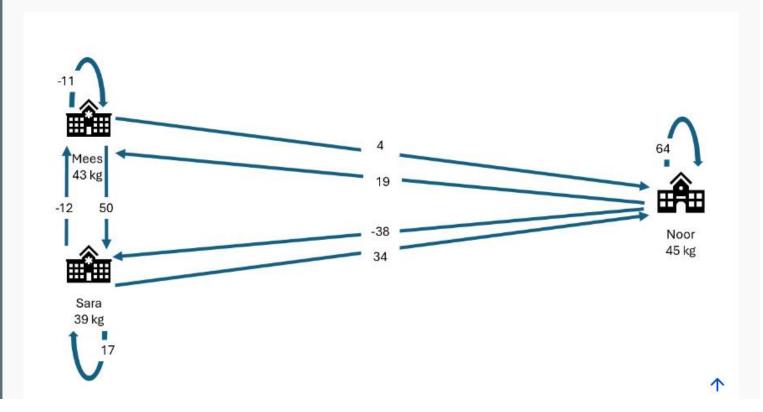


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SECRET SHARING, AN EXAMPLE

Mees, Sara and Noor want to know how much they weigh in total. Mees weighs 43 kg, Sara weighs 39, Noor weighs 45. All three they think of 2 random numbers r_1 and r_2 so that $weight=r_1+r_2+x$. Finally they compute x by $x=weight-r_1-r_2$

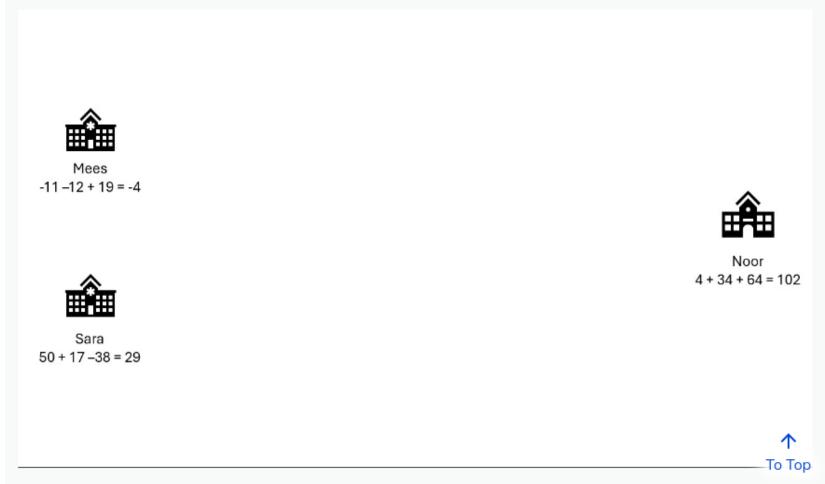
After computing the secret shares, they distribute these "cryptographical puzzle pieces" among their peers.





Secret sharing: an example

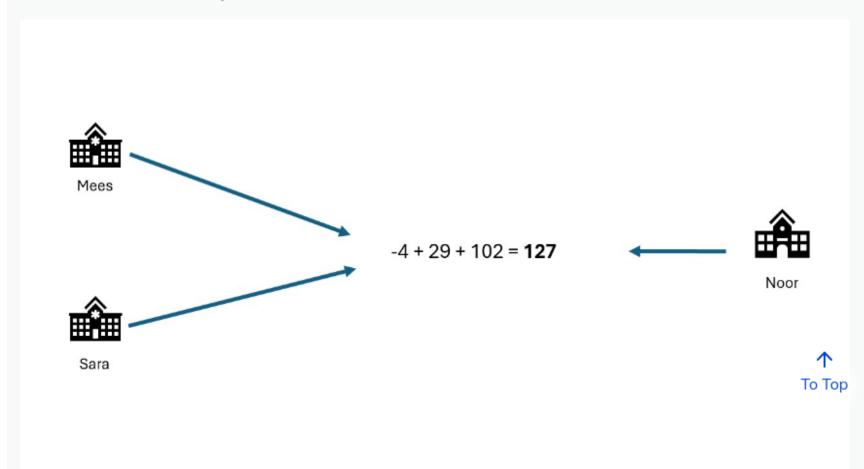




Secret sharing: an example



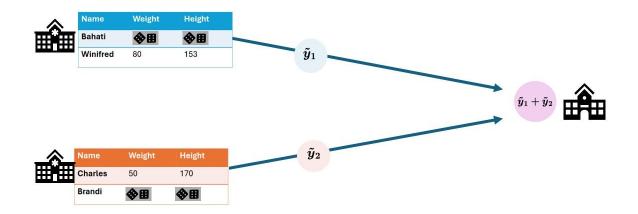
They add their sums together: -4 + 29 + 102 = 127 In this way, they have aggregated their data without sharing their individual data with anyone else.





Differential privacy: Add noise







Data partitioning



Horizontal partitioning

Name	Weight	Height
Charles	50	170
Brandi	45	163



Name	Weight	Height
Jez	33	193
Deonne	25	168

Vertical partitioning

Name	Weight
Bahati	20
Winifred	80
Ben	62
Zayden	18

Name	Height	
Bahati	180	
Winifred	153	
Ben	198	
Zayden	182	





Projects usually combine techniques







Technology doesn't solve everything!



- Privacy enhancing technology is only a small part of the data sharing puzzle
- Some other factors
 - Trust
 - Regulations (either general or specific to the location)
 - Data harmonization

