CONTRIBUTIONS TO DECENTRALIZED AND PRIVACY-PRESERVING MACHINE LEARNING
HABILITATION THESIS (HDR) DEFENSE

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Design ML algorithms that take into account societal and ethical issues.
WHAT DRIVES MY RESEARCH

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Make ML algorithms accessible to citizens, so they can collectively define their own usage
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- **Decentralized ML**: learn collaboratively while keeping control of your data
- **Privacy-preserving ML**: ensure ML does not leak your sensitive data
- **Fair ML**: ensure ML model does not discriminate or is not overly biased
- **Speech privacy**: use voice interfaces without being personally identifiable
- **Transparent & reproducible ML**
- **Open source development**
## What Drives My Research

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- **Decentralized ML**: learn collaboratively while keeping control of your data
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- **Transparent & reproducible ML**
- **Open source development**
WHAT IS DECENTRALIZED AND PRIVACY-PRESERVING MACHINE LEARNING?
FROM CENTRALIZED TO DECENTRALIZED DATA

• The standard setting in ML considers a *centralized dataset* processed in a tightly integrated system.
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• The standard setting in ML considers a **centralized dataset** processed in a tightly integrated system

• But in the real world **data is often decentralized** across many parties
WHY CAN’T WE JUST CENTRALIZE THE DATA?

1. Sending the data may be too costly
   - Self-driving cars are expected to generate several TBs of data a day
   - Some wireless devices have limited bandwidth/power
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2. Data may be considered too sensitive to be shared
   - We see a growing public awareness and regulations on data privacy
   - Keeping control of data can give a competitive advantage in business and research
HOW ABOUT EACH PARTY LEARNING ON ITS OWN?

1. The local dataset may be **too small**
   - Sub-par predictive performance (e.g., due to overfitting)
   - Non-statistically significant results (e.g., medical studies)
HOW ABOUT EACH PARTY LEARNING ON ITS OWN?

1. The local dataset may be too small
   - Sub-par predictive performance (e.g., due to overfitting)
   - Non-statistically significant results (e.g., medical studies)

2. The local dataset may be biased
   - Not representative of the target distribution
Decentralized learning (also called federated learning) aims to collaboratively train ML models while keeping data decentralized.

→ shared exploitation of the data rather than sharing the data itself.
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→ shared exploitation of the data rather than sharing the data itself

- When I started working on this in 2015-2016, it was a newly emerging topic
- It is now in a booming phase\(^1\)

\(^1\)https://www.forbes.com/sites/robtoews/2020/10/12/the-next-generation-of-artificial-intelligence/
DECENTRALIZED LEARNING: TYPICAL PROCESS

initialize model
DECENTRALIZED LEARNING: TYPICAL PROCESS

each party makes an update using its local dataset
DECENTRALIZED LEARNING: TYPICAL PROCESS

parties share local updates for aggregation
DECENTRALIZED LEARNING: TYPICAL PROCESS

server aggregates updates and sends back to parties
parties update their copy of the model and iterate
CHALLENGE 1: DEALING WITH DATA HETEROGENEITY

• Decentralized learning comes with many challenges, distinct from those of classic distributed ML on a cluster (see our collaborative survey [Kairouz et al., 2021])
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CHALLENGE 1: DEALING WITH DATA HETERGENEITY

- Decentralized learning comes with many challenges, distinct from those of classic distributed ML on a cluster (see our collaborative survey [Kairouz et al., 2021])

- Local datasets are often highly heterogeneous, because they reflect the usage and production patterns specific to each party

- Challenges: design low-communication decentralized algorithms that scale to many parties and learn models that are useful to all users
• Not sharing data is insufficient to obtain robust privacy guarantees
CHALLENGE 2: PROTECTING PRIVACY

- Not sharing data is insufficient to obtain robust privacy guarantees
- Information about training individual training points can be extracted from a trained model [Shokri et al., 2017, Paige et al., 2020]
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• Decentralized learning offers an additional attack surface because the server and/or other parties observe model updates (not only the final model)

• **Challenges:** design decentralized learning algorithms with rigorous privacy guarantees while minimizing the impact on the utility of the resulting models
FOCUS ON TWO SETS OF CONTRIBUTIONS

1. Decentralized Learning of **Personalized Models**

2. **Better Privacy-Utility Trade-offs** for Decentralized Learning
Decentralized Learning of Personalized Models
• A set of *n users* who behave honestly (i.e., follow the protocol)

• Each user *u* holds a dataset $\mathcal{D}_u$ of $m_u$ data points, and we let $m = \sum_u m_u$

• Models with parameters $\theta$ (e.g., weights of a linear classifier or neural network)

• A standard objective is to learn a **global model** by solving a problem of the form

$$\arg\min_{\theta} \sum_{u=1}^{n} \frac{m_u}{m} F_u(\theta; \mathcal{D}_u)$$
• We propose to learn personalized models $\Theta = (\theta_1, \ldots, \theta_n)$ and a similarity graph represented by pairwise weights $w = (w_{u,v})_{u<v}$ by solving

$$\arg\min_{\Theta,w \geq 0} \sum_{u=1}^{n} \frac{m_u}{m} F_u(\theta_u; \mathcal{D}_u)$$

• Trade-off between learning accurate models on local data

\[ d_u(w) = \sum_{v \neq u} w_{u,v} \]
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\arg \min_{\Theta, w \geq 0} \sum_{u=1}^{n} d_u(w) \frac{m_u}{m} F_u(\theta_u; D_u) + \frac{\lambda_1}{2} \sum_{1 \leq u < v \leq n} w_{u,v} \|\theta_u - \theta_v\|^2
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- Trade-off between learning accurate models on local data and learning similar models for similar users (the degree \( d_u(w) = \sum_{v \neq u} w_{u,v} \) is a normalizing factor)
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- Trade-off between learning accurate models on local data and learning similar models for similar users (the degree $d_u(w) = \sum_{v \neq u} w_{u,v}$ is a normalizing factor)
- Captures flexible relationships: hyperparameter $\lambda_1 \geq 0$ interpolates between learning purely local models and a shared model per connected component
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• Captures flexible relationships: hyperparameter $\lambda_1 \geq 0$ interpolates between learning purely local models and a shared model per connected component

• Graph regularizer $g(w)$: avoid trivial graph, encourage sparsity
• We remove the need for a central server: instead, each user communicates with a small number of neighbors in a network graph.
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→ Naturally scales to many users (as long as network graph is sparse)
• We will solve the problem by alternating optimization over $\Theta$ and $w$. 
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• For fixed graph $w$, we design an algorithm to optimize the models $\Theta$ where each user $u$ communicates only with its neighborhood in $w$: $\mathcal{N}(u) = \{v : w_{u,v} > 0\}$
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• At step $t \geq 0$, a random user $u$ becomes active:
  1. user $u$ combines a weighted average of neighbors’ models and a local gradient step:

     $$\theta_u(t + 1) = (1 - \alpha)\theta_u(t) + \alpha \left( \sum_{v \in \mathcal{N}(u)} \frac{w_{u,v}}{d_u(w)} \theta_v(t) - \frac{m_u}{\lambda_1 m} \nabla F_{u}(\theta_u(t); \mathcal{D}_u) \right)$$

  2. user $u$ sends its updated model $\theta_k(t + 1)$ to its neighborhood $\mathcal{N}(k)$
Reminder of the objective: \[
\sum d_u(w) \frac{m_u}{m} F_u(\theta_u; D_u) + \frac{\lambda_1}{2} \sum w_{u,v} \|\theta_u - \theta_v\|^2 + \lambda_2 g(w)
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- We avoid having isolated users and control the graph sparsity with the regularizer:
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g(w) = -1^T \log(d(w)) + \lambda_3 \|w\|^2
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- At step \( t \geq 0 \), a random user \( u \) becomes active:
  1. Use peer sampling to contact a set \( V \) of \( \rho \) users, request their model and degree
  2. Update the weights with users in \( V \) via a gradient update
  3. Send each user \( v \in V \) the updated weight \( w(t + 1)_{u,v} \)
Theorem (Convergence rates, informal [Bellet et al., 2018, Zantedeschi et al., 2020])

Let $J(\Theta, w)$ be the joint objective.
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1. For fixed $w$, let $M(\Theta) = J(\Theta, w)$. There exists $\kappa > 0$ such that for any $T > 0$:

$$\mathbb{E} \left[ M(\Theta(T)) - M^* \right] \leq \left( 1 - \frac{\kappa}{n} \right)^T (M(\Theta(0)) - M^*).$$

2. For fixed $\Theta$, let $G(w) = J(\Theta, w)$. There exists $\kappa' > 0$ such that for any $T > 0$:

$$\mathbb{E} \left[ G(w(T)) - G^* \right] \leq \left( 1 - \frac{\rho \kappa'}{n(n-1)} \right)^T (G(w(0)) - G^*).$$
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EMPIRICAL RESULTS

• On heterogeneous data, our approach typically outperforms both global and purely local models
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• Our formulation can **learn complex relationships between users**
We proposed to learn personalized models in a fully decentralized setting:

- We modeled relationships between users by a sparse similarity graph
- We leveraged this graph to learn better personalized models for each user
- We jointly optimized the models and the graph

→ the first method for personalized decentralized learning: this has become a standard approach to deal with heterogeneous data
BETTER PRIVACY-UTILITY TRADE-OFFS FOR DECENTRALIZED LEARNING
Definition (Dwork et al., 2006, informal) \(A\) is \((\epsilon, \delta)\)-DP if for all neighboring datasets \(D = \{x_1, x_2, \ldots, x_n\}\) and \(D' = \{x_1, x'_2, x_3, \ldots, x_n\}\) and all possible sets of outputs \(S\):

\[
\Pr[A(D) \in S] \leq e^{\epsilon} \Pr[A(D') \in S] + \delta.
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**Definition ([Dwork et al., 2006], informal)**

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• **Central DP**: a trusted curator collects raw data and runs a DP algorithm $\mathcal{A}$ on it $\rightarrow$ the output $\mathcal{A}(\mathcal{D})$ is only the final result

• **Local DP**: there is no trusted curator so each user must locally randomize its contributions $\rightarrow$ the output $\mathcal{A}(\mathcal{D})$ consists of all messages sent by all users

• Local DP is a suitable model for decentralized learning without trusted parties but, for a fixed $(\epsilon, \delta)$-DP guarantee, its utility cost is typically $\sqrt{n}$ larger $\rightarrow$ study intermediate models allowing better utility without relying on trusted parties
TRUST MODELS: CENTRAL DP VERSUS LOCAL DP

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$\rightarrow$ study intermediate models allowing better utility without relying on trusted parties
· In most decentralized algorithms with a server, interaction is needed only to aggregate local updates → this is the step we need to make private
A KEY FUNCTIONALITY: DP AGGREGATION

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- **Differentially private aggregation:** given a private value $\theta_u \in [0, 1]$ for each user $u$, we want to accurately estimate $\theta^{\text{avg}} = \frac{1}{n} \sum_u \theta_u$ under an $(\epsilon, \delta)$-DP constraint.
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- **Central DP**: trusted server computes $\theta^{avg}$ and adds Gaussian noise

- **Local DP**: each user $u$ adds (more) Gaussian noise to $\theta_u$ before sharing it
Assume that pairs of users are able to exchange encrypted messages (the server may act as relay): this can be achieved e.g. through a public key infrastructure.
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**Algorithm**  GOPA protocol [Sabater et al., 2020]

Each user $u$ generates independent Gaussian noise $\eta_u$. 

$$\hat{\theta}_u = \theta_u + \sum_{u \sim v} \Delta_{u,v} + \eta_u$$ 

Estimate of the average:

$$\hat{\theta}_{\text{avg}} = \frac{1}{n} \sum_u \hat{\theta}_u = \theta_{\text{avg}} + \frac{1}{n} \sum_u \eta_u$$
GOPA PROTOCOL FOR DP AGGREGATION

- Assume that pairs of users are able to exchange encrypted messages (the server may act as relay): this can be achieved e.g. through a public key infrastructure

Algorithm  GOPA protocol [Sabater et al., 2020]

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Each user $u$ selects a random set of $k$ other users
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Algorithm  GOPA protocol [Sabater et al., 2020]

Each user $u$ generates independent Gaussian noise $\eta_u$
Each user $u$ selects a random set of $k$ other users
for all selected pairs of users $u \sim v$ do
  Users $u$ and $v$ securely exchange pairwise-canceling Gaussian noise $\Delta_{u,v} = -\Delta_{v,u}$
• Assume that pairs of users are able to exchange encrypted messages (the server may act as relay): this can be achieved e.g. through a public key infrastructure

**Algorithm** GOPA protocol [Sabater et al., 2020]

- Each user $u$ generates independent Gaussian noise $\eta_u$
- Each user $u$ selects a random set of $k$ other users
- **for all** selected pairs of users $u \sim v$ **do**
  - Users $u$ and $v$ securely exchange pairwise-canceling Gaussian noise $\Delta_{u,v} = -\Delta_{v,u}$
- Each user $u$ sends $\hat{\theta}_u = \theta_u + \sum_{u \sim v} \Delta_{u,v} + \eta_u$ to the server

**Estimate of the average:**

$$\hat{\theta}_{\text{avg}} = \frac{1}{n} \sum_u \hat{\theta}_u = \theta_{\text{avg}} + \frac{1}{n} \sum_u \eta_u$$
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• Estimate of the average: \( \hat{\theta}^{avg} = \frac{1}{n} \sum_u \hat{\theta}_u = \theta^{avg} + \frac{1}{n} \sum_u \eta_u \)
• **Adversary**: coalition of the server with a proportion $1 - \tau$ of the users
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**Theorem (Privacy of GOPA [Sabater et al., 2020], informal)**

- Let each user select $k = O(\log(\tau n) / \tau)$ other users
- Set the independent noise variance so as to satisfy $(\epsilon, \delta')$-DP in the central model
- For large enough pairwise noise variance, GOPA is $(\epsilon, \delta)$-DP with $\delta = O(\delta')$.  


• Adversary: coalition of the server with a proportion $1 - \tau$ of the users

Theorem (Privacy of GOPA [Sabater et al., 2020], informal)

- Let each user select $k = O(\log(\tau n)/\tau)$ other users
- Set the independent noise variance so as to satisfy $(\epsilon, \delta')$-DP in the central model
- For large enough pairwise noise variance, GOPA is $(\epsilon, \delta)$-DP with $\delta = O(\delta')$.

• Same utility as central DP with only logarithmic number of messages per user
• In fully decentralized learning, there is no global aggregation step
HOW ABOUT FULLY DECENTRALIZED ALGORITHMS?

- In fully decentralized learning, there is **no global aggregation** step
- But there is **no server observing all messages**, and each user $u$ has a limited view

![Diagram showing the view of party $u$.](image)

Question:
- Can this be used to prove stronger differential privacy guarantees?

Motivated by previous work on private rumor spreading [Bellet et al., 2020]
HOW ABOUT FULLY DECENTRALIZED ALGORITHMS?

• In fully decentralized learning, there is **no global aggregation** step

• But there is **no server observing all messages, and each user** $u$ **has a limited view**

• **Question**: can this be used to **prove stronger differential privacy guarantees**?

• Motivated by previous work on private rumor spreading [Bellet et al., 2020]
• Let $O_u$ be the set of messages sent and received by user $u$
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**Definition (Network DP [Cyffers and Bellet, 2020])**

An algorithm $A$ satisfies $(\epsilon, \delta)$-network DP if for all pairs of distinct users $u, v \in \{1, \ldots, n\}$ and all pairs of datasets $D, D'$ that differ only in the local dataset of user $v$, we have:

$$\Pr[O_u(A(D))] \leq e^{\epsilon} \Pr[O_u(A(D'))] + \delta.$$

This is a relaxation of local DP: if $O_u$ contains the full transcript of messages, then network DP boils down to local DP.
• Consider the standard objective $F(\theta; D) = \frac{1}{n} \sum_{u=1}^{n} F_u(\theta; D_u)$ and a complete graph.
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We consider a decentralized algorithm where the model is updated sequentially by following a random walk.

**Algorithm**  Private decentralized SGD on a complete graph

- Initialize model $\theta$
- **for** $t = 1$ to $T$ **do**
  - Current user updates $\theta$ by a gradient update with Gaussian noise
  - Current user sends $\theta$ to a random user
- **return** $\theta$
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WALK-BASED DECENTRALIZED SGD

- Consider the standard objective $F(\theta; \mathcal{D}) = \frac{1}{n} \sum_{u=1}^{n} F_u(\theta; \mathcal{D}_u)$ and a complete graph
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- We show some robustness to collusion (albeit with smaller privacy amplification).
We proposed decentralized methods that nearly match the utility of central DP:

1. We designed a aggregation protocol for decentralized learning with a server
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2. We showed how to exploit the limited view of users in fully decentralized algorithms → the first work to show that full decentralization can amplify privacy guarantees, providing a new motivation for such algorithms beyond scalability
PUTTING DECENTRALIZED LEARNING TO PRACTICE
CHALLENGE 3: REAL DEPLOYMENTS

• *Technological challenges*: develop general-purpose software libraries which can be easily deployed in production systems
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- **Regulatory/legal challenges**: when should model updates be considered as personal data? how to ensure compliance with current regulations (e.g., GDPR)?
CHALLENGE 3: REAL DEPLOYMENTS

- **Technological challenges**: develop general-purpose software libraries which can be easily deployed in production systems.
- **Regulatory/legal challenges**: when should model updates be considered as personal data? how to ensure compliance with current regulations (e.g., GDPR)?
- **Convincing stakeholders**: what are the key merits of decentralized learning for a given application? how to make it as transparent as possible to the end-users?
We are currently exploring these questions with Lille University Hospital in the context of my project FLAMED.

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2 https://www.cnil.fr/fr/bac-sable-donnees-personnelles-la-cnil-accompagne-12-projets-dans-le-domaine-de-la-sante-numerique
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• We have some official support from CNIL (the French Data Protection Authority) on legal aspects (such as writing DPIAs)²

²https://www.cnil.fr/fr/bac-sable-donnees-personnelles-la-cnil-accompagne-12-projets-dans-le-domaine-de-la-sante-numerique
FUTURE RESEARCH

RELATED TOPICS
“Improve DP guarantees at no cost in utility by exploiting the way information is exchanged in fully decentralized ML”

(4-year grant funded by the French National Research Agency, started in 2021)

Three complementary research directions:

1. (Broadening the scope of) privacy amplification by decentralization
2. Secure multi-party computation meets decentralized algorithms
3. Data-adaptive decentralized communication
Show that fully decentralized algorithms amplify privacy in a variety of settings

- General and time-evolving topologies to balance privacy, scalability and robustness
- Algorithms allowing more parallel computation
- Lower bounds on the error achievable under network DP
- Further relaxations, e.g. when each user may trust a few peers in the network

→ PhD of Edwige Cyffers
Combine secure multi-party computation (MPC) and decentralized algorithms

- Decentralized algorithms that use **MPC primitives in local steps**

- Trade-offs between **computation, communication and privacy** ruled by the number of parties involved in local steps

  ➔ Postdoc (to hire) + collaborations with MPC experts like **Adrià Gascón**
Design data-adaptive topologies for faster convergence under heterogeneous data

- **Optimization of the topology** under statistical assumptions on data heterogeneity
- **General types of heterogeneity**, extending our work on label skew [Bellet et al., 2021]
- **Dynamic adaptation** of the topology while learning

→ Postdoc of **Batiste Le Bars** + collaboration with computing systems team at EPFL
An Inria-wide project on decentralized learning
→ Coordinated by G. Neglia and myself, to start in 2022

• Foster collaborations between Inria teams on this topic

• Multidisciplinary: ML, optimization, privacy & security, networks, systems...
Future Research

Broader topics
• Achieving better privacy-utility trade-offs in private optimization may be possible by making additional assumptions on the problem structure

• We have recently started considering finer coordinate-wise regularity assumptions [Mangold et al., 2021]

• Assumptions about the structure of the optimal solution (such as sparsity) are promising directions to tackle high-dimensionality

→ PhD of Paul Mangold
• Rich signals like speech, images, and text embed various types of information

• We typically want to protect specific modalities (e.g., personal attributes of the writer) while fully retaining others (e.g., the meaning of the text)

• Formal notions like DP are necessary to get clear guarantees, but need to be relaxed and combined with techniques from representation learning and signal processing

  → PhD of Gaurav Maheshwari (text), PhD of Jean-Rémy Conti (images)
THANK YOU FOR YOUR ATTENTION!
Who started this rumor? Quantifying the natural differential privacy guarantees of gossip protocols.
In DISC.

Personalized and Private Peer-to-Peer Machine Learning.
In AISTATS.

D-Cliques: Compensating for Data Heterogeneity with Topology in Decentralized Federated Learning.

Privacy Amplification by Decentralization.

Calibrating noise to sensitivity in private data analysis.
In Theory of Cryptography (TCC).
REFERENCES


