Challenges in Privacy-Preserving Learning for Collaborative Research Consortia

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Collaborative research on human health

There are many data sharing challenges in human health research:

• Secondary use of clinical data for research: can we use existing hospital records for tasks such as comparative effectiveness research?

• Designing multi-site studies: multi-site clinical trials, meta-analyses on original data, etc.

• **Collaborative research/data sharing initiatives to get population statistics from research subjects.**
Research consortia for human health

Research consortia are common in many research areas involving human health:

• focused on specific conditions: Alzheimer’s, autism, breast cancer, etc.

• strong mandate to share data (e.g. from the NIH)

• significant concerns about privacy and ethics
Privacy technologies can help research consortia

Offering privacy protections can incentivize researchers to join research consortia:

- Allow research groups to hold and maintain “control” over their data.
- Need to design software systems to allow consortium members to run analyses.
- What is “privacy” in this context?
State of the art: ENIGMA

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The ENIGMA Network brings together researchers in imaging genomics to understand brain structure, function, and disease, based on brain imaging and genetic data.
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- Improve reproducibility, sample sizes by allowing easier meta-analyses.
- Example: genetic variation associated with intercranial and hippocampal volumes.
- 30+ working groups on a wide range of conditions and topics.

http://enigma.ini.usc.edu
ENIGMA Workflow

- Study proposal is approved by ENIGMA managers.
- Analyses performed on local sites and emailed to ENIGMA manager as Excel spreadsheets.
- Manager has to perform "manual" meta-analysis.
Collaborative Informatics Neuroimaging Suite

• End-to-end system for managing data for studies on the brain

• Current usage: 37,903 participants in 42,961 scan sessions from 612 studies for a total of 486,955 clinical assessments.

• Data from 34 states, 38 countries
COINSTAC

Extend COINS to allow automated analyses:

- register data sets in COINSTAC
- perform automated analyses using message passing
- data held locally, analyses run automatically
Typical applications

Focus on popular neuroimaging tools:

• Feature learning: ICA, IVA, NMF, deep learning…

• Regression and classification: ridge regression, LASSO, SVM, etc.

• Visualization: t-SNE, network visualization, etc.
What about privacy?

What sort of privacy can we guarantee in a system like COINSTAC?

- hand-waving: “data is held locally”
- formal: develop DP algorithms for neuroimaging tasks
Building DP into COINSTAC

• Designing decentralized/distributed versions of some of these algorithms is sometimes open.

• Given a distributed algorithm, we can apply “the DP toolkit” to make a DP version.

• “Utility first” approach to setting $\varepsilon$. 
Challenges

Types of challenges in using DP:

- Statistical
- Definitional
- Algorithmic
- Policy
Small n, large p

The goal is to leverage multiple data sets to get larger sample size to learn about the population:

• Number of samples is still small. MRIs are big.

• Constants matter, log factors matter.

• Algorithm performance is very data dependent.

• How can we understand non-asymptotic performance?
Types of algorithms

Much of the work in differentially private learning has been driven by trends in “big data:”

• Other domains often have preferred tools/methods.

• Visualization is very important.

• How should we expand the “basic toolkit” to allow easier development of these tools?
ε- versus (ε, δ)-DP

Practitioners want stronger privacy guarantees: δ = 0.

• Risk averse: nonzero δ is seen as unacceptable.

• Practically: choosing δ ≈ 1/n destroys utility.

• Strong composition rules are nice, but may not help as much: can we get better (ε, 0) algorithms or help make smaller δ practical?
Multi-stage algorithms

Computational analyses in neuroimaging involve processing *pipelines*:

- Many (or all) stages need to guarantee DP.
- How should we think about allocating privacy risk across stages? Is there something better than empirical?
- Pipelines are used more than once: can we reuse parameter tuning to ease overall privacy loss?
Prior domain knowledge

Domain experts either “know” or assume “w.l.o.g.” many things about their data:

• Priors are a good way to incorporate this information, but knowledge may not be explicitly encoded Bayes-style.

• Restricting the data domain (or database schema) seems like a good start, but many prior assumptions are about the “population.”

• What kind of property testing methods should we use/develop? Is local sensitivity enough?
Trust models in consortia

Research consortia have different trust models and assumptions.

• Extreme view 1: everyone is trusted here, this is just between “friends” etc.

• Extreme view 2: I’m not going to let those #$%^## look at my hard-earned data.

• In reality, we operate somewhere in between…
Less pessimistic models

Much of the utility loss comes from conservative (strong) threat modeling in DP:

• Real workflows will require significant interaction with the data

• Privacy budgets may need to be renewed, privacy restrictions may expire.

• Are there some relaxations or different threat models (or modified privacy definitions) that are appropriate for these systems?
Lessons learned

• Good application domains have (i) mandate or desire for data sharing that is (ii) hampered by privacy concerns

• Not all algorithms/problems may be appropriate for differential privacy (at least for now).

• Accept large $\varepsilon$, at least initially.
Thank you!

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