Differential Privacy: Data Curation and Theoretical Work

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• Controls the excess risk to an individual from participating in an analysis.
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• Rich theoretical foundation; in prime time for testing and application.
• Receives interest from many communities.
Differential Privacy [DMNS 2006]

Formally,

A randomized mechanism $M : X^n \rightarrow T$ is (pure) $\epsilon$-differentially private if for all neighboring datasets $x, x' \in X^n$ and subset $S$ of the outcome set $T$,

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$$\Pr[M(X) \in S] \leq e^\epsilon \cdot \Pr[M(X') \in S] + \delta$$

Relaxation: approximate differential privacy also allows a (negligible) additive difference, $\delta$. 
What can be computed with DP?

A huge variety of computational tasks:

• Basic statistics.
  ▶ Histograms, contingency tables, CDFs, …

• Inferential statistics.
  ▶ Regression, …

• Machine learning.
  ▶ Classification, clustering, SVD, convex optimization, …

• Graph/social network analysis.

• Streaming algorithms.
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Broader applications: Where privacy is not necessarily the goal

• Mechanism design, games.
• Preventing false detection.
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Prototype Tool for Differentially Private Data Exploration
Figure: The curator architecture for data privacy.
workflow for private data

https://beta.dataverse.org/custom/
DifferentialPrivacyPrototype/
### Summer 2015 Efforts

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<thead>
<tr>
<th>Problem</th>
<th>Social Science</th>
<th>Computer Science</th>
<th>Statistics</th>
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<tbody>
<tr>
<td>Regression</td>
<td>Mentor</td>
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<td>Utility</td>
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<td>Antuca</td>
<td>Wang</td>
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<td>Two-way Tables</td>
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<td>Gooden</td>
<td>Rogers</td>
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<td>Lim</td>
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<tr>
<td>Density and Trees</td>
<td>Honaker</td>
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<tr>
<td>Security Architecture</td>
<td>(Durand)</td>
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<td>Interactive Queries</td>
<td></td>
<td></td>
<td>Kaminsky</td>
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<td>Datalog Logic Engine</td>
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<td></td>
<td>Bembenek</td>
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<td>Attacks on Agg. Data</td>
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<td>Jiang</td>
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Figure: Example screen from the interactive privacy budget allocation tool for data depositors.
The TwoRavens Interface
Figure: Privacy architecture for secure curator interfaces.
Integration with Zelig
This prototype system will allow researchers with sensitive datasets to make differentially private statistics about their data available through data repositories using the Dataverse platform.


This system was created by the Privacy Tools for Sharing Research Data project. Differential privacy is a mathematical framework for enabling statistical analysis of sensitive datasets while ensuring that individual-level information cannot be leaked. The project website contains resources for learning more about differential privacy.

**Budget Tool**

The first part of this system is a tool that helps both data depositors and data analysts distribute a global privacy budget across many statistics. Users select which statistics they would like to calculate and are given estimates of how accurately each statistic can be computed. They can also redistribute their privacy budget according to which statistics they think are most valuable in their dataset. This work has motivated new theoretical results from our group that maximize the utility achievable when using differential privacy to share many statistics about a research dataset.

**Curator Interface**

When the data depositor has distributed their privacy budget, the second portion of our tool system draws differentially private versions of those statistical summaries selected by the data depositor from a library of differentially private routines (which we created in the R statistical language, and also make available for use by the R community) and stores them in metadata associated with that file on Dataverse. Future researchers who wish to explore restricted social science data can then access these privacy-preserving summary statistics either from the metadata, or through the Two Ravens graphical data exploration tool built for Dataverse, which we have adapted for differentially private statistics.

**Interactive Queries**

Our system will allow some of the privacy budget to be reserved for future data analysts to choose their own differentially private statistics to calculate (selected from the library of differentially private algorithms provided by the system). Differential privacy will ensure that even if these queries are chosen adversarially, individual-level information will not be leaked. This currently works through a command-line interactive system, and we are developing a future user interface.

This system was created by the Privacy Tools for Sharing Research Data project. Here are ways you can follow or contribute to this project.

https://beta.dataverse.org/custom/DifferentialPrivacyPrototype/
Differential Privacy
Theoretical Research
Main Focus Areas

- **DP and statistics** [D’Orazio, Gaboardi, Honaker, Karwa, King, Lim, Rogers, Sheffet, Vadhan, Zheng].
- **Private machine learning** [Bun, Nissim].
- **Bounds on DP** [Bun, Nissim, Vadhan].
- **DP and false discovery** [Nissim, Smith, Steinke, Ullman].
- **Programming languages techniques for DP** [Gaboardi].
- **Composition of DP mechanisms** [Murtagh, Vadhan].
- **A new real-life application** [Kantarcioglu, Sweeney].
- **Estimating privacy risk** [Dwork, Jiang, Smith, Steinke, Ullman, Vadhan].
- **DP as an equilibrium of economic games** [Chen, Nissim, Sheffet, Vadhan].
DP and Statistics

- [Sheffet]: New DP algorithms for 2nd moment matrix of dataset and least-squares regression for statistical inference.

- [D'Orazi, Hnaker, King and Karwa, Vadhan]: Working on regression.

- [Gaboardi, Lim, Rügers]: New results on goodness-of-fit testing and independence testing with DP. In particular, how to calculate "significance level" of test, taking into account added noise for DP.

- [Vadhan, Zheng]: Traditional synthetic data generation methods achieved differential privacy in many cases. Zheng's thesis won the Hades Prize for outstanding undergraduate work. Karwa is a outstanding researcher with Airldi. Airldi & Nissim were readers in Zheng's thesis.
DP and Statistics

• Linear Regression & Casual Inference:
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*Karwa is a post-doc researcher with Airoldi & Vadhan. Airoldi & Nissim were readers on Zheng’s Thesis.
New Real-Life Applications of DP

• In first site visit Sweeney introduced a re-identification of bicycle routes in Hubway contest.

[Kantarcioglu, Sweeney]: Compared DP techniques to create synthetic datasets. I showed that DP would have sufficed for most entries in Hubway dataset with $\epsilon = 0$.

• Over the next year, they will test the actual utility of these methods against contest entries.

Goal: redesign software to contest organizers worldwide to use.
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- [Steinke, Ullman COLT15]: extend lowerbound techniques for DP to give tight bounds on computational hardness of preventing false discovery.
- [Nissim, Smith, Steinke, Ullman+]: Give improved upperbounds for false discovery and a tight characterization of the generalization of DP.
Bounds on DP

• Part of our long-term research on understanding what can be computed with DP, and with what costs.

• [Bun, Nissim, Vadhan+ FOCS15]: Estimating basic statistics such as quantiles, learning distributions wrt Komogorov distance on domain $D$.
  - Requires between $\log^* |D|$ and $2^{\log^* |D|}$ samples.
  - Impossible when information is taken from a continuous domain.
Private Machine Learning

- Part of our long-term research of possibility and limitations of DP machine learning.
- [Nissim+ SODA15]: Semi-supervised learning (where some examples are unlabeled) for mitigating the higher sample complexity of DP learning.
  - Number of labeled examples matches non-private learning.
- [Bun, Nissim+]: Upper- and lower-bounds on the cost of simultaneously learning $k$ concepts.
PL techniques for DP

• Part of our long-term research into PL tools for ensuring differential privacy.
• [Gaboardi+ POPL15]: Semi-automated techniques for verifying a program is DP.
  ▶ based on a type system able to express properties of two runs of a program
• [Gaboardi+ SNAPL15]: Formal program logic techniques for reasoning about randomized algs.
  ▶ Useful, in particular, for expressing and verifying accuracy properties of DP mechanisms.
Composition of DP mechanisms

• Part of our long-term goal of understanding and using composition of DP mechanisms.
  ➤ Composition is one of the properties making DP programmable.
• [Murtagh, Vadhan] Optimal composition theorems for DP.
  ➤ Hardness of exactly computing the optimal composition.
  ➤ Poly-time approximation of optimal composition.
Estimating Privacy Risk

- [Dwork, Smith, Steinke, Ullman, Vadhan FOCS15]: New attacks on releases of aggregate stats.
  - Require less auxiliary information than previous similar attacks.
  - Use very simple stats (column sums).
  - Robust to choice of perturbation technique.
- [Jiang, Steinke] perform experimental evaluation of the attacks.
DP as an equilibrium of economic games

- Does DP appear naturally in games?
- [Chen, Sheffet, Vadhan WINE14]: Analyzed a simple game-theoretic model where an agent balances benefits and risks of revealing sensitive information.
- Research in this vein continues (+Nissim).
DP - New papers (since Jan 2015)

• Mark Bun, Jonathan Ullman, Salil Vadhan. Fingerprinting Codes and the Price of Approximate Differential Privacy. SICOMP.
• Amos Beimel, Kobbi Nissim, Uri Stemmer. Learning Privately with Labeled and Unlabeled Examples. SODA.
• Mark Bun, Kobbi Nissim, Uri Stemmer, Salil Vadhan. Differentially Private Release and Learning of Threshold Functions. FOCS.
• Or Sheffet. Private Approximations of the 2nd-Moment Matrix Using Existing Techniques in Linear Regression.
• Or Sheffet. Differentially Private Least Squares: Estimation, Confidence and Rejecting the Null Hypothesis.
• Jack Murtagh, Salil Vadhan. The Complexity of Computing the Optimal Composition of Differential Privacy.
• Mark Bun, Mark Zhandry. Order-Revealing Encryption and the Hardness of Private Learning.
• Thomas Steinke, Jonathan Ullman. Interactive Fingerprinting Codes and the Hardness of Preventing False Discovery. COLT.
• Thomas Steinke, Jonathan Ullman. Between Pure and Approximate Differential Privacy.
• Raef Bassily, Adam Smith, Thomas Steinke, Jonathan Ullman. More General Queries and Less Generalization Error in Adaptive Data Analysis.
• Kobbi Nissim, Uri Stemmer. On the Generalization Properties of Differential Privacy.
• Kobbi Nissim, Uri Stemmer, Salil Vadhan. Locating a Small Cluster Privately.
• Mark Bun, Kobbi Nissim, Uri Stemmer. Simultaneous Private Learning of Multiple Concepts.
• Cynthia Dwork, Adam Smith, Thomas Steinke, Jonathan Ullman, Salil Vadhan. Robust Traceability from Trace Amounts. FOCS.
• Xianrui Meng, Seny Kamara, Kobbi Nissim, George Kollios. GRECS: Graph Encryption for Approximate Shortest Distance Queries. ACM CCS.
DP - Selected Presentations

• Privacy Tools participates in TPDP Workshop as program chair, committee, and invited speaker.
• Kobbi Nissim: Privacy: How theory can influence reality. UCSD Distinguished Lecturer Series.
• Vito D’Orazio, James Honaker, Garry King: Differentially private methods. Annual Meetings of the American Political Science Association and Meetings of the Midwest Political Science Association.
• Thomas Steinke: Differential Privacy. China Theory Week.
• Kobbi Nissim: The Theory of Bringing Privacy into Practice. Caltech.
• Kobbi Nissim: private learning. Charles River Crypto Day
• Mark Bun: Differentially Private Release and Learning of Threshold Functions. FOCS.
• Thomas Steinke: Robust Traceability from Trace Amounts. FOCS.
• Vito D’Orazio, James Honaker, Gary King and co-PI King presented on differentially private methods at the Meetings of the Midwest Political Science Association.
Some future research directions

• Linear regression and causality inference.
• Improvements in S&A - a basic DP construction technique.
• Often issues w.r.t. privacy learning in linear DP: Characterization of sample complexity, imprecision learning, ...
• Adaptive technique of parameters.
• Data-based choice of DP mechanism.
• Controlling false discovery in adaptive data analysis.
• DP where privacy is not the goal.
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- The use of differentially private tools requires new ways of thinking about our statistical estimators.
- Our theoretical work has helped establish and advance the rich theory that makes differential privacy a strong privacy concept.