Future research plan as a postdoctoral fellow

My training in probability, statistics, convex analysis, information theory, and statistical physics has led me to explore problems in privacy, unlearning, and beyond during my PhD. In the coming years, I plan to build on these to tackle concrete problems that cut across privacy, fairness, spin glasses, and quantum aspects of computation and learning, trying to merge the ideas of statistics and economics into the science of AI.

A highlight of my current work includes resolving a conjecture proposed in the celebrated Gaussian differential **privacy** paper and introducing an entirely new formulation of Poisson differential privacy that is naturally suited for count statistics on (random) graphs, along with providing an optimal mechanism to achieve it.

I am also developing a statistical framework of quantum differential privacy based on non-commutative Fourier analysis (representation theory) to provide provable security guarantees for **quantum computation**.

In a separate line of work, motivated by problems in **spin glasses**, I have established a multivariate version of the celebrated Ghirlanda–Guerra identities as a consequence of Panchenko's invariance principle that was used to establish ultrametricity. As an application, I have derived an exact expression for the limiting moments for the (entrywise heavily dependent) matrix of spin–spin correlations for mean field spin glass *at all temperatures*.

Now, I outline several research directions I hope to pursue in the coming years during this appointment. My recent work has convinced me that the fundamental notion of **Blackwell informativeness** provides a unifying mathematical language for seemingly distant problems aimed at quantifying information.

- **Graph differential privacy.** My recent work on infinitely divisible privacy (IDP) [9], proposes a Poisson differential privacy (PDP) framework that is well-suited for count statistics, such as the degree sequence of a graph. We then provide an optimal mechanism to achieve it, going far beyond the popular noise-adding mechanism to achieve Gaussian DP (GDP) [4]. It would be interesting to apply the PDP framework to statistical models such as the exponential random graph model (ERGM) [6], and analyze the privacy-accuracy trade-offs, determine whether PDP can be achieved with a dimension-free noise. Finally, it is practically relevant to extend the theory of the IDP framework to include a priori adaptive number of private operations through Wald–Wolfowitz's sequential probability ratio test framework [12] encompassing limit theorems beyond the IDP framework.

- **Gaussian certified machine unlearning with first order methods.** *Efficient erasability of influence of requested data* is a requirement for a trained ML model [1]. The unlearning algorithm in my work on Gaussian certified unlearning [11] was a second-order Newton method. So, from the practical viewpoint, a natural question is to analyze Gaussian certifiability of a first-order method such as (stochastic) gradient descent. More concretely, I aim to achieve this with summary statistic approach taken in [2, 3].

- **Differential privacy meets mechanism design.** *Mechanism design* offers the language (through revelation principle [8]) for data-driven central institutions (designer) to utilize individuals' (agent) private information to the fullest, whereas differential privacy ensures provable guarantees for agent's data during the interaction with the designer. More concretely, given the recent advancement in achieving *mechanism design with limited commitment* [5], I am extremely interested in analyzing what happens to the designer's optimal mechanisms once we put another constraint that the agent only releases differentially private outcomes of her private information with Blackwell baseline trade-off function f [4]. On a related note, an immediate consequence of my results on IDP [9] combined with [4] finds a characterization of all **Lorenz** curves describing wealth inequality, along with a characterization of the class of infinitely divisible Lorenz curves, which appears as a limit of a newly defined product of Lorenz curves [9]. Moreover, the techniques of [7] characterize the extreme points of the convex region of trade-off functions above a Blackwell baseline trade-off function f.

- **Algorithmic aspects of quantum differential privacy.** With the advent of quantum technologies, a statistical approach to quantum hypothesis testing is becoming essential in fields including quantum computing, information, and cryptography. In my current work on quantum differential privacy [10], I am interested in investigating the algorithmic side of how much privacy a given CPTP map (such as quantum algorithms that are often used in the practice of quantum computation) can provide under my f-QDP framework. On a related note, I am interested in developing a quantum analogue of **Blackwell's theorem** to make my f-QDP framework robust. Moreover, it remains an interesting question to generalize (or find a class of counterexamples) the quantum central limit theorem of my current work [10], along the lines of its classical version [4], on how the baseline privacy curves converge in the limit of a large number of quantum computations.

- **The spin correlation matrix of the perceptron model.** My work on obtaining exact expressions for the limiting moments of the spin correlation matrix $M_N = (\langle \sigma_i \sigma_j \rangle_\mu)_{i,j=1}^N$ for mean field spin glasses naturally leads to the following fascinating question of analyzing the moments of the spin correlation matrix for the perceptron, where the underlying Hamiltonian H_N changes its mathematical form to $H_N(\sigma) = \sum_{i=1}^N u(\langle g_i, \sigma \rangle)$ with random directions $\{g_i\}$, a potentially non-concave function u, and the Gibbs measure $\mu_N(\sigma) \propto e^{\beta H_N(\sigma)}$ [13, 14].

[1] John M. Abowd. "The U.S. Census Bureau Adopts Differential Privacy". In: ACM, 2018. DOI: 10.1145/3219819.3226070. URL: https://dl.acm.org/doi/10.1145/3219819.3226070.

[2] Gérard Ben Arous, Reza Gheissari, and Aukosh Jagannath. "High-dimensional limit theorems for SGD: Effective dynamics and critical scaling". In: *CPAM* (2024). DOI: 10.1002/cpa.22169.

[3] Gérard Ben Arous et al. "Spectral alignment of stochastic gradient descent for high-dimensional classification tasks". In: *AAP* (2025). DOI: 10.1214/25-AAP2187.

[4] Jinshuo Dong, Aaron Roth, and Weijie J. Su. "Gaussian Differential Privacy". In: *JRSS: Series B* (2022). DOI: 10.1111/rssb.12454. URL: https://academic.oup.com/jrsssb/article/84/1/3/7056089.

[5] Laura Doval and Vasiliki Skreta. "Mechanism Design With Limited Commitment". In: *Econometrica* (2022). DOI: 10.3982/ECTA16846. URL: https://doi.org/10.3982/ECTA16846.

[6] Vishesh Karwa and Aleksandra B. Slavković. "Inference Using Noisy Degrees: Differentially Private β-Model and p_0-Model". In: *The Annals of Statistics* (2016). DOI: 10.1214/15-AOS1358.

[7] Andreas Kleiner, Benny Moldovanu, and Philipp Strack. "Extreme Points and Majorization: Economic Applications". In: *Econometrica* (2021). DOI: 10.3982/ECTA18312. URL: https://doi.org/10.3982/ECTA18312.

[8] Roger B. Myerson. "Optimal Coordination Mechanisms in Generalized Principal–Agent Problems". In: *Journal of Mathematical Economics* (1982). DOI: 10.1016/0304-4068(82)90006-4. URL: https://doi.org/10.1016/0304-4068(82)90006-4.

[9] Aaradhya Pandey, Arian Maleki, and Sanjeev Kulkarni. "Infinitely Divisible Privacy and Beyond: Resolution of the $s^2 = 2k$ Conjecture". 2025. URL: https://arxiv.org/abs/2512.00734.

[10] Aaradhya Pandey, Arian Maleki, and Sanjeev Kulkarni. "Quantum f-Differential Privacy: A Hypothesis Testing Approach and a central limit theorem". Manuscript in preparation. 2025.

[11] Aaradhya Pandey et al. "Gaussian Certified Unlearning in High Dimensions: A Hypothesis Testing Approach". In: (2025). Submitted. DOI: 10.48550/arXiv.2510.13094. URL: https://arxiv.org/abs/2510.13094.

[12] Yury Polyanskiy and Yihong Wu. *Information Theory: From Coding to Learning*. Cambridge University Press, 2025. DOI: 10.1017/9781108966351. URL: https://doi.org/10.1017/9781108966351.

[13] Michel Talagrand. *Mean field models for spin glasses. Volume I: Basic examples*. A Series of Modern Surveys in Mathematics. Springer, 2011. DOI: 10.1007/978-3-642-15202-3.

[14] Michel Talagrand. *Mean field models for spin glasses. Volume II: Advanced replica-symmetry and low temperature*. A Series of Modern Surveys in Mathematics. Springer, 2011. DOI: 10.1007/978-3-642-22253-5.