Personal research statement: My research has primarily been on topics in information theory, statistics, and machine learning. My doctoral research was on the topic of mathematical inequalities in information theory, where I introduced novel information-theoretic inequalities inspired by convex geometry [1]. These innovations found applications in solving complex problems within information theory, such as determining the capacity of energy harvesting channels [2]. My dissertation received the prestigious Eli Jury Award from UC Berkeley's EECS department, and I earned the Best Student Paper award at the International Symposium on Information Theory in 2015 [3, 4]. As as Assistant Professor at UW-Madison, my research on information-theoretic inequalities was supported by a $150,000 research grant from the National Science Foundation in 2019.

After completing my PhD, my research shifted toward statistical problems, particularly in random graph theory. I was one of the early contributors to the problem of community detection in the stochastic block model [5]. My co-authored work on weighted stochastic block models was published in the Annals of Statistics [6]. My research on time-evolving random graphs identified "persistent phenomena," inspiring novel algorithms for detecting sources of infections and rumors [7, 8]. This research was supported by a $175,000 grant from the National Science Foundation. I continue to work on topics at the intersection of probability and graph theory. I will spend part of my sabbatical at SLMath (previously MRSI, Berkeley) where I am invited to participate in a workshop on random graphs from Jan-May 2025.

While an Assistant Professor at UW-Madison, I got intrigued by neural networks and their generalization and robustness properties. I co-authored a paper that employed information-theoretic techniques to derive generalization error bounds for a broad class of algorithms [9, 10]. This work was at the forefront of a broader trend of research that established information theory as a valuable tool in theoretical machine learning. My group's contributions to adversarial robustness, linking it with optimal transport theory, were published in prominent conferences and journals [11, 12, 13, 14]. In recognition of my work, the National Science Foundation honored me with a CAREER Award in 2020, providing $500,000 over five years for my research in information theory and machine learning. I was also invited to participate in workshops on deep learning and generalization at the Simons Institute in Berkeley, in 2019 and 2024, as a long-term visitor.

In January 2021, I joined the Department of Pure Mathematics and Mathematical Statistics (DPMMS) at the University of Cambridge as an Assistant Professor in the Mathematics of Information and Learning. This move renewed my focus on core theoretical problems in information theory and statistics. My recent work, funded by a £55,000 grant from the Isaac Newton Trust, centers on proving instance-optimal, non-asymptotic, sample complexity bounds for different hypothesis testing problems of interest [15, 16, 17]. Hypothesis testing is one the most exciting areas for information-theoretic methods in statistics with many unexplored research directions. I expect these will form the core of my research for the coming years.

I have always been keen to apply my research to problems of practical significance. I co-founded the Machine Learning for Medical Imaging initiative at UW-Madison, fostering interdisciplinary collaborations between medical researchers and statisticians. As one of three principal investigators, I helped secure a 4-year, $1,300,000 grant from the National Institutes of Health in 2020 to investigate robust learning algorithms in medical imaging. This initiative has led to numerous publications in well-regarded conferences and journals [18, 19]. I continue to provide guidance as a consultant on this project while based in Cambridge.

References

[1] Jog, V. (2015). Convex geometric tools in information theory.

[2] Jog, V., & Anantharam, V. (2016). A Geometric Analysis of the AWGN channel with a (σ, ρ)-Power Constraint. IEEE Transactions on Information Theory, 62(8), 4413-4438.

[3] Jog, V., & Anantharam, V. (2015, June). On the geometry of convex typical sets. In 2015 IEEE International Symposium on Information Theory (ISIT) (pp. 829-833). IEEE.

[4] Jog, V., & Anantharam, V. (2017). Intrinsic entropies of log-concave distributions. IEEE Transactions on Information Theory, 64(1), 93-108.

[5] Jog, V., & Loh, P. L. (2015, September). Recovering communities in weighted stochastic block models. In 2015 53rd Annual Allerton Conference on Communication, Control, and Computing (Allerton) (pp. 1308-1315). IEEE.

[6] Xu, M., Jog, V., & Loh, P. L. (2020). Optimal rates for community estimation in the weighted stochastic block model. Annals of Statistics, 2020, 183-204.

[7] Jog, V., & Loh, P. L. (2018). Persistence of centrality in random growing trees. Random Structures & Algorithms, 52(1), 136-157.

[8] Jog, V., & Loh, P. L. (2016). Analysis of centrality in sublinear preferential attachment trees via the Crump-Mode-Jagers branching process. IEEE Transactions on Network Science and Engineering, 4(1), 1-12.

[9] Pensia, A., Jog, V., & Loh, P. L. (2018, June). Generalization error bounds for noisy, iterative algorithms. In 2018 IEEE International Symposium on Information Theory (ISIT) (pp. 546-550). IEEE.

[10] Lopez, A. T., & Jog, V. (2018, November). Generalization error bounds using Wasserstein distances. In 2018 IEEE Information Theory Workshop (ITW) (pp. 1-5). IEEE.

[11] Pydi, M. S., & Jog, V. (2021). The many faces of adversarial risk. Advances in Neural Information Processing Systems, 34, 10000-10012.

[12] Pydi, M. S., & Jog, V. (2020, November). Adversarial risk via optimal transport and optimal couplings. In International Conference on Machine Learning (pp. 7814-7823). PMLR.

[13] Pydi, M. S., & Jog, V. (2023). The many faces of adversarial risk: An expanded study. IEEE Transactions on Information Theory.

[14] Pydi, M. S., & Jog, V. (2021). Adversarial Risk via Optimal Transport and Optimal Couplings. IEEE Transactions on Information Theory, 67(9), 6031-6052.

[15] Pensia, A., Jog, V., & Loh, P. L. (2022). Communication-constrained hypothesis testing: Optimality, robustness, and reverse data processing inequalities. To appear in IEEE Transactions on Information Theory, 2024.

[16] Pensia, A., Asadi, A. R., Jog, V., & Loh, P. L. (2023, July). Simple binary hypothesis testing under local differential privacy and communication constraints. In The Thirty Sixth Annual Conference on Learning Theory (pp. 3229-3230). PMLR.

[17] Pensia, A., Jog, V., & Loh, P. L. (2023, July). The sample complexityuof simple binary hypothesis testing. Working paper.

[18] Liu, Z., Zhang, J., Jog, V., Loh, P. L., & McMillan, A. B. (2021). Robustifying deep networks for medical image segmentation. Journal of Digital Imaging, 34, 1279-1293.

[19] Gurbani, S., Morgan, D., Jog, V., Dreyfuss, L., Shen, M., Das, A., Lubner, M. G. (2021). Evaluation of radiomics and machine learning in identification of aggressive tumor features in renal cell carcinoma (RCC). Abdominal Radiology, 46, 4278-4288.