Curriculum Vitae

First name	**Tiangang**
Last name	**Cui**

1 Work Experience

2023–present	Senior Lecturer School of Mathematics and Statistics, University of Sydney, Australia.
2020–2023	Senior Lecturer School of Mathematics, Monash University, Australia.
2016–2020	Lecturer School of Mathematics, Monash University, Australia.
2015–2016	Engineer Upstream Research Company, ExxonMobil Corporation, USA.
2012–2015	Postdoctoral Associate, Department of Aeronautics and Astronautics Massachusetts Institute of Technology, USA.
2011–2012	Partner Otago Computational Modelling Group Ltd, New Zealand.

2 Education

2006–2010	Ph.D., Engineering Science, The University of Auckland, New Zealand Thesis: *Bayesian Calibration of Geothermal Reservoir Models via MCMC* Ph.D. thesis awarded place on Dean's list
2004–2006	Master of Engineering, Engineering Science, The University of Auckland, New Zealand First Class Honours, GPA 9.0/9.0
2001–2004	Bachelor of Science, Applied Mathematics, The University of Auckland, New Zealand Senior Scholarship in Applied Mathematics (ranked 1st place in the program), GPA 8.7/9.0

3 Publications

Total citation: 2005 (source: Google Scholar). H-index: 20. Citation since 2020: 1384. Bian, Chen, Polishchuk, Wang, Wu, and Zhao are my past and current students. Detommaso is my past visiting student.

$*$ indicates a publication since I joined the University of Sydney.

† indicates a publication since my last promotion.

3.1 Journal publications

[1] *,†**T. Cui**, J. Dick and F. Pillichshammer (2025). Quasi-Monte Carlo methods for mixture distributions and approximated distributions via piecewise linear interpolation, *Advances in Computational Mathematics*, 51 (10), doi:10.1007/s10444-025-10223-1.

[2] *,†**T. Cui** and F. Pillichshammer (2025). Bernstein approximation and beyond: proofs by means of elementary probability theory, *Elemente der Mathematik*, in press, doi:10.4171/EM/548.

[3] *,†**T. Cui**, J. Dong, A. Jasra and X. T. Tong (2025). Convergence speed and approximation accuracy of numerical MCMC, *Advances in Applied Probability*, 57(1), 101–133.

[4] *,†**T. Cui**, G. Detommaso, R. Scheichl (2024). Multilevel dimension-independent likelihood-informed MCMC for large-scale inverse problems, *Inverse Problems*, 40, 035005.

[5] *,†**T. Cui**, H. De Sterck, A. D. Gilbert, S. Polishchuk and R. Scheichl (2024). Multilevel Monte Carlo methods for stochastic convection-diffusion eigenvalue problems, *Journal of Scientific Computing*, 99(3), 1–34.

[6] *,†Y. Zhao and **T. Cui** (2024). Tensor-train methods for sequential state and parameter learning in state-space models, *Journal of Machine Learning Research*, 25 (244), 1–51.

[7] *,†**T. Cui**, S. Dolgov, and R. Scheichl (2024). Deep importance sampling using tensor trains with application to *a priori* and *a posteriori* rare event estimation, *SIAM Journal on Scientific Computing*, 46(1), C1–C29.

[8] *,†**T. Cui**, Z. Wang, and Z. Zhang (2023). A variational neural network approach for glacier modelling with nonlinear rheology, *Communications in Computational Physics*, 34(4), 934–954.

[9] †**T. Cui**, S. Dolgov, O. Zahm (2023). Scalable conditional deep inverse Rosenblatt transports using tensor-trains and gradient-based dimension reduction, *Journal of Computational Physics*, 485, 112103.

[10] †**T. Cui**, S. Dolgov (2022). Deep composition of tensor trains using squared inverse Rosenblatt transports, *Foundations of Computational Mathematics*, 22(6), 1863–1922.

[11] †**T. Cui**, X. T. Tong and O. Zahm (2022). Prior normalization for certified likelihood-informed subspace detection of Bayesian inverse problems, *Inverse Problems*, 38(12), 124002.

[12] †**T. Cui**, X. T. Tong (2022). A unified performance analysis of likelihood-informed subspace methods, *Bernoulli*, 28(4), 2788–2815.

[13] †O. Zahm, **T. Cui**, K. Law, Y. Marzouk, and A. Spantini (2022). Certified dimension reduction in nonlinear Bayesian inverse problems, *Mathematics of Computation*, 91(336), 1789–1835.

[14] †**T. Cui**, O. Zahm (2021). Data-free likelihood-informed dimension reduction of Bayesian inverse problems, *Inverse Problems*, 37 (4), 045009.

[15] †L. Bian, **T. Cui**, B.T. Yeo, A. Fornito, A. Razi, J. Keith (2021). Identification of brain states, transitions, and communities using functional MRI, *NeuroImage*, 244, 118635.

[16] †J. Bardsley, **T. Cui** (2021). Optimization-based MCMC methods for nonlinear hierarchical statistical inverse problems, *SIAM/ASA Journal on Uncertainty Quantification*, 9(1), 29–64.

[17] †J. Bardsley, **T. Cui**, Y. Marzouk, Z. Wang (2020). Scalable optimization-based sampling on function space, *SIAM Journal on Scientific Computing*, 42(2), A1317–A1347.

[18] †C. Fox, **T. Cui**, M. Neumayer (2020). Randomized reduced forward models for efficient Metropolis–Hastings MCMC, with application to subsurface fluid flow and capacitance tomography, *GEM-International Journal on Geomathematics*, 11(1), 1–38.

[19] †R. Brown, J. Bardsley, **T. Cui** (2020). Semivariogram hyper-parameter estimation for Whittle-Matérn priors in Bayesian inverse problems, *Inverse Problems*, 36(5), 055006.

[20] †S. Wu, **T. Cui**, X. Zhang, T. Tian (2020). A non-linear reverse-engineering method for inferring genetic regulatory networks, *PeerJ*, 8, e9065.

[21] **T. Cui**, C. Fox, C., M. O'Sullivan (2019). Adaptive error modelling for large scale inverse problem–A posteriori stochastic correction of reduced models in delayed–acceptance MCMC, with application to multiphase subsurface inverse problems, *International Journal for Numerical Methods in Engineering*, 118(10), 578–605.

[22] **T. Cui**, C. Fox, G. Nicholls, M. O'Sullivan (2019). Using parallel Markov chain Monte Carlo to quantify uncertainties in geothermal reservoir calibration, *International Journal for Uncertainty Quantification*, 9(3), 295–310.

[23] S. Thiele, L. Grose, **T. Cui**, S. Micklethwaite, A. Cruden (2019). Extraction of high-resolution structural orientations from digital data: A Bayesian approach, *Journal of Structural Geology*, 122, 106–115.

[24] C. Reboul, S. Kiesewetter, M. Eager, M. Belousoff, **T. Cui**, H. De Sterck, D. Elmlund, H. Elmlund (2018). Rapid near-atomic resolution single-particle 3D reconstruction with SIMPLE, *Journal of Structural Biology*, 204(2), 172–181.

[25] Z. Wang, Y. Marzouk, J. Bardsley, **T. Cui**, and A. Solonen (2017). Bayesian inverse problems with l_1 priors: a randomize-then-optimize approach, *SIAM Journal on Scientific Computing*, 39(5), S140–S166.

[26] A. Spantini, **T. Cui**, K. Willcox, L. Tenorio and Y. Marzouk (2017). Goal-oriented optimal approximations of Bayesian linear inverse problems, *SIAM Journal on Scientific Computing*, 39(5), S167–S196.

[27] **T. Cui**, Y. Marzouk, and K. Willcox (2016). Scalable posterior approximation for large-scale inverse problems, *Journal of Computational Physics*, 315, 363–387.

[28] A. Solonen, **T. Cui**, J. Hakkarainen and Y. Marzouk (2016). On dimension reduction in Bayesian filtering, *Inverse Problems*, 32(4), 045003.

[29] **T. Cui**, K. H. L. Law and Y. M. Marzouk (2016). Dimension-independent likelihood-informed MCMC, *Journal of Computational Physics*, 304(1), 109–137.

[30] B. Peherstorfer, **T. Cui**, Y. Marzouk and K. Willcox (2016). Multifidelity importance sampling, *Computer Methods in Applied Mechanics and Engineering*, 300, 490–509.

[31] A. Spantini, A. Solonen, **T. Cui**, J. Martin, L. Tenorio and Y. M. Marzouk (2015). Optimal low-rank approximation of linear Bayesian inverse problems, *SIAM Journal on Scientific Computing*, 37(6), A2451–A2487.

[32] **T. Cui**, N. Dudley Ward, S. Eveson and T. Lähivaara (2015). Pragmatic approach to calibrating distributed parameter groundwater models from pumping test data using adaptive delayed acceptance MCMC, *ASCE Journal of Hydrologic Engineering*, 21(2), 06015011.

[33] **T. Cui**, Y. M. Marzouk and K. E. Willcox (2015). Data-driven model reduction for the Bayesian solution of inverse problems, *International Journal for Numerical Methods in Engineering*, 102(5), 966–990.

[34] **T. Cui**, J. Martin, Y. M. Marzouk, A. Solonen and A. Spantini (2014). Likelihood-informed dimension reduction for nonlinear inverse problems, *Inverse Problem*, 30, 114015.

[35] **T. Cui**, N. Dudley Ward and J. Kaipio (2013). Characterisation of parameters for a spatially heterogenous aquifer from pumping test data, *ASCE Journal of Hydrologic Engineering*, 19(6), 1203–1213.

[36] **T. Cui**, N. Dudley Ward (2013). Uncertainty quantification in stream depletion tests, *ASCE Journal of Hydrologic Engineering*, 18(12), 1581–1590.

[37] **T. Cui**, C. Fox and M. J. O'Sullivan (2011). Bayesian calibration of a large scale geothermal reservoir model by a new adaptive delayed acceptance Metropolis Hastings algorithm, *Water Resource Research*, 47(10), W10521.

3.2 Peer–reviewed conference proceedings and book chapters

[38] L. Bian, **T. Cui**, G. Sofronov, J. Keith (2020). Network structure change point detection by posterior predictive discrepancy, *Monte Carlo and Quasi-Monte Carlo Methods 2018*, Springer, 107–123.

[39] J. Bardsley, **T. Cui** (2019). MCMC methods for nonlinear, hierarchical-Bayesian inverse problems, *In: 2017 MATRIX Annals (editors: David R. Wood, Jan de Gier, Cheryl Praeger, Terence Tao), Springer*, 3–12.

[40] N. Ye, F. Roosta-Khorasani, **T. Cui** (2019). Optimization methods for inverse problems, *In: 2017 MATRIX Annals (editors: David R. Wood, Jan de Gier, Cheryl Praeger, Terence Tao), Springer*, 121–140.

[41] G. Detommaso, **T. Cui**, Y. Marzouk, A. Spantini, R. Scheichl (2018). A Stein variational Newton method, *Advances in Neural Information Processing Systems*, 8130.

[42] S. Wu, **T. Cui**, T. Tian (2018). Mathematical modelling of genetic network for regulating the fate determination of hematopoietic stem cells, *2018 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, 2167–2173.

3.3 Invited news articles

[43] **T. Cui** and C. Fox (2010). Computational inference for inverse problems, Annotated Bibliography, *The ISBA Bulletin*, 17(3).

3.4 Patents

[44] "Conditioning Method and System for Channel Lobe Deposition Environment." (2024). U.S. Patent 12105241.

3.5 Journal manuscripts under review

[45] **T. Cui**, K. Koval, R. Herzog and R. Scheichl, Subspace accelerated measure transport methods for fast and scalable sequential experimental design, with application to photoacoustic imagings. arXiv:2502.20086

[46] N. Mueller, Y. Zhao, S. Badia, **T. Cui**, A tensor-train reduced basis solver for parameterized partial differential equations. arXiv:2412.14460

[47] **T. Cui**, A. Gorodetsky, Low-rank Bayesian matrix completion via geodesic Hamiltonian Monte Carlo on Stiefel manifolds. arXiv:2410.20318

[48] **T. Cui**, S. Liu, X. Tong, ℓ_∞-approximation of localized distributions. arXiv:2410.11771

[49] M.T.C. Li, **T. Cui**, F. Li, Y. Marzouk, O. Zahm, Sharp detection of low-dimensional structure in probability measures via dimensional logarithmic Sobolev inequalities. arXiv:2406.13036

[50] **T. Cui**, O. Zahm, and X. Tong, Optimal Riemannian metric for Poincaré inequalities and how to ideally precondition Langevin dymanics. arXiv:2404.02554

[51] B. Zanger, O. Zahm, **T. Cui** and M. Schreiber, Sequential transport maps using SoS density estimation and α-divergences. arXiv:2402.17943

[52] **T. Cui**, S. Dolgov, and O. Zahm, Self-reinforced polynomial approximation methods for concentrated probability densities. arXiv:2303.02554

3.6 Manuscripts in preparation

[53] C. Chen, **T. Cui**, Y. Marzouk, Multilevel acceleration for optimization-based sampling methods.

[54] **T. Cui**, J. Dong, A. Jasra, X. Tong, Computational strategy for replica exchange methods for Bayesian inverse problems.

[55] K. Kim, **T. Cui**, B. Peherstorfer, N. Petra, Joint parameter and state dimension reduction for Bayesian inversion of ice sheet dynamics.

4 Research Grants and Fellowships

Since my last promotion in 2020, my research has been supported by the following research funding and fellowships:

1. 2025. J. Tinsley Oden Faculty Fellow at the Oden Institute for Computational Engineering & Sciences (8,000 USD), UT Austin, USA.

2. 2025. IMS Workshop on "Efficient Sampling Algorithms for Complex Models" (90,000 SGD), supported by the Institute for Mathematical Sciences (IMS), Singapore (with X. Tong).

3. 2023–2024. Romberg Visiting Scholar (15,000 Euro), Heidelberg University, Germany.

4. 2021–2023. Interface-aware numerical methods for stochastic inverse problems (475,000.00 AUD), Australian Research Council (ARC) DP210103092, Chief Investigator (joint CIs: S. Badia).

5. 2018–2021. Enabling 3D stochastic geological modelling (711,000.00 AUD), Australian Research Council (ARC) LP170100985, Chief Investigator (the grant is awarded to a team consists of 9 researchers from Monash University and the University of Western Australia).

In the past, I have also received support from the following funding sources.

6. 2019. ACEMS research support scheme (20,000 AUD), ARC Centre of Excellence for Mathematical & Statistical Frontiers.

7. 2018. Monash Suzhou Research Incubator Program (MSRIP) Fund (5000 AUD), Monash-SEU Alliance.

8. 2017. MATRIX program on "Computational Inverse Problems" (58,500 AUD), supported by MATRIX, AMSI and ANZIAM (with H. De Sterck, M. Hegland, Y. Marzouk, I. Turner, K. Willcox).

9. 2017. Mathematics for cryogenic electron microscopy: understanding the present and shaping the future (28,676 AUD), Faculty of Science and Faculty of Medicine, Nursing and Health Sciences (MNHS) Interdisciplinary Research Seed Fund project, Monash University (with H. Elmlund and H. De Sterck).

I have also participated in the following externally funded projects, centers and networks:

- 2023–2028. "Australia France Network of Doctoral Excellence (AUFRANDE)", €15.7 million, European Union, Marie Skłodowska-Curie Grant Agreement No 101081465.

  AUFRANDE is a joint PhD training hub led by RMIT Europe, involving 37 universities across France and Australia, with Monash as a participating partner. I joined the project (with guaranteed PhD positions) and served as the coordinator for Monash. My role was discontinued due to relocation.

- 2020–2023. Collaborator on "Advanced data fusion methods for environmental modeling (ADA-FUME)", total €1,400,000, Academy of Finland, Finland. Principal Investigators: M. Laine and S. Särkkä.

- 2017–2021. Associated Investigator of the "ARC Centre of Excellence for Mathematical & Statistical Frontiers" (ACEMS), CE140100049.

5 Teaching

5.1 Courses developed

1. Computational Linear Algebra for Machine Learning, Romberg Short Course for graduate students (15 lecture hours), Heidelberg University.

2. Computational Linear Algebra (MTH3320), with De Sterck, Monash University.

3. Computational Statistical Inference (MTH5089), with Keith, Monash University.

4. Statistical Machine Learning, 2018 Australian Mathematical Sciences Institute (AMSI) Summer School.

5.2 Courses taught at the University of Sydney

1. MATH1062/MATH1005 Mathematics 1B: 2024 S1, 2024 S2, 2025 S1.
   - Class size: 400 to 1500 students.

2. STAT5002 Introduction to Statistics: 2024 S2, 2025 S1.
   - Class size: 200 to 300 students.

3. STAT4028 Mathematical Statistics: 2024 S1, 2025 S1.
   - Class size: 5 to 20 students.

5.3 Courses taught at Monash

Average teaching evaluation score as an instructor: 4.5/5.

1. MTH3320 Computational Linear Algebra: 2017, 2018, 2019, 2020, 2021, 2022.
   - Class size: 30 to 50 students.
   - MTH3320 was officially recognised as one of the most satisfactory units by the Student Evaluation of Teaching and Units (SETU) in 2019. Only 7.3% of all Monash units received this recognition.

2. MTH5089 Computational Statistical Inference: 2018, 2019, 2020, 2021, 2022.
   - Class size: 10 to 20 students.

3. MTH5321 Methods of Computational Mathematics: 2018, 2019, 2020, 2021, 2022.
   - Class size: 30 to 50 students.
   - This class also has the unit code MTH5530 "Computational Methods in Finance".

4. MTH1020 Analysis of Change: 2021.
   - Class size: approximately 200 students.

5. ENG2005 Advanced Engineering Mathematics: 2017, 2018.
   - Class size: over 300 students.

5.4 Other Invited Courses

1. Invited lecturer of "Computational Linear Algebra for Machine Learning" as a part of Romberg Fellowship, Heidelberg University, 2024.

2. Invited lecturer of "Statistical Machine Learning" at the 2018 AMSI Summer School.

3. Organising committee member of 2017 AMSI Winter School.

6 Research Supervision

6.1 Postdocs

1. Yiran Zhao (USyd), DP210103092, 2024–2025.

2. Simon Kiesewetter (Monash), 2017–2018, co-supervised with De Sterck and Elmlund.

6.2 PhD students

1. Thanh Dat Tran (main supervisor, USyd). Starting date: 2024

2. Alex De Beer (main supervisor, USyd). Starting date: 2024

3. Yiran Zhao (main supervisor, Monash). Completion date: 04/2024. First position: postdoc researcher at the University of Sydney.

4. Chuntao Chen (main supervisor, Monash). Thesis: Multilevel optimisation-based sampling methods for Bayesian inverse problems. Completion date: 06/2022. First position: postdoc researcher at the Lappeenranta-Lahti University of Technology, Finland.

5. Stanislav Polishchuk (main supervisor, Monash). Thesis: Advanced multi-level and multi-index Monte Carlo methods in uncertainty quantification. Completion date: 03/2022.

6. Siyuan Wu (co-supervisor, Monash). Thesis: Mathematical and computational methods for analyzing genetic regulation of cell fate determination in hematopoiesis. Completion date: 01/2022. First position: Lecturer at James Cook University, Australia.

7. Oliver Krzysik (main supervisor, Monash). Thesis: Multilevel parallel-in-time methods for advection-dominated PDEs. Completion date: 11/2021. First position: postdoc researcher at the University of Waterloo, Canada.

8. Lingbin Bian (co-supervisor, Monash). Thesis: Bayesian change-point detection for dynamic functional brain networks. Completion date: 09/2021. First position: Assistant Researcher at ShanghaiTech University, China.

9. Zheng Wang (co-supervisor, MIT). Thesis: Scalable optimization-based sampling in function space for Bayesian inverse problems. Completion date: 05/2019. First position: Software Engineer at KaleidoGlobe, USA.

6.3 Master and Honours students

- Primary supervisor of 2 Master students: A. Yu (completed in 2018) and Y. Zhao (completed in 2019).

- Co-supervisor of 2 Master students: A. Musolas (MIT, completed in 2016) and N. Kartik (MIT, completed in 2013).

- Supervisor of 4 Honours students: Natasha Stanbridge (2025), Steven Lin (2025), Thanh Tran (2022) and Samuel Schneider (2018).

7 Professional Activities

7.1 Editorial services

- *Foundations of Data Science*, Associate Editor.
- Journal referee: *SIAM Journal on Scientific Computing*, *SIAM/ASA Journal on Uncertainty Quantification*, *Journal of Computational Physics*, *Inverse Problems*, *Journal of the American Statistical Association*, *Statistics and Computing*, *Computer Methods in Applied Mechanics and Engineering*, *Computers & Geosciences*, *AIAA Journal*, *Entropy*, *Advances in Water Resources*, *Journal of Hydrologic Engineering*, *Journal of the Optical Society of America A*

7.2 PhD examination

- Ariel Vidal Diaz, The University of Auckland, New Zealand, 2017
- Jericho Omagbon, The University of Auckland, New Zealand, 2018
- Owen Dillon, The University of Auckland, New Zealand, 2019
- Harriet Li, Massachusetts Institute of Technology, USA, 2019

7.3 External committees

- 2020 - 2024, Executive Committee Member, Computational Mathematics Group, Australia and New Zealand Industrial and Applied Mathematics.

7.4 Major conference and workshop organisations

1. Organiser, MATRIX program on “Theoretical and Computational Foundations of Sequential Learning”, MATRIX Institute, Australia, 17-28 Nov 2025.
2. Organiser, IMS Workshop on “Efficient Sampling Algorithms for Complex Models”, Institute for Mathematical Sciences (IMS), Singapore, 14-25 July 2025.
3. The Third New Zealand Workshop on Uncertainty Quantification and Inverse Problems. Auckland, New Zealand. 18-22 February 2025
4. Organising committee member, SIAM Conference on Computational Science and Engineering (CSE23), Amsterdam, The Netherlands, 2023.
5. Organiser, 9th Workshop on High-Dimensional Approximation, Australian National University, February, 2023.
6. Organiser, MATRIX program on “Computational Inverse Problems”, MATRIX Institute, Australia, July, 2017.

7.5 Symposium organisations at international research conferences

1. Stochastic and Deterministic Inverse Problems (with Graff and Hosseini), *Joint Meeting of the NZMS, AustMS and AMS*, Auckland, New Zealand, 2024.
2. Mathematical Methods for Scientific Machine Learning, *International Conference on Scientific Computation and Differential Equations*, National University of Singapore, Singapore, 2024.
3. Theoretical and computational advances in measure transport (with Baptista, Marzouk and Doucet), *International Congress on Industrial and Applied Mathematics (ICIAM)*, Tokyo, Japan, 2023.
4. Uncertainty Quantification for High-Dimensional Inverse Problems, *SIAM Conference on Uncertainty Quantification (UQ22)*, Atlanta, Georgia, U.S., 12 –15 April, 2022.
5. Computational Strategies for High Dimensional Stochastic Problems (with Tong), *SIAM Conference on Computational Science and Engineering (online)*, Originally scheduled in Fort Worth, Texas, USA, 2021.

6. Multilevel and Multi-fidelity Methods for Model-Based Statistical Learning (with Badia, Gilbert, Marzouk, Scheichl), *SIAM Conference on Uncertainty Quantification (cancelled due to COVID19)*, Garching, Germany, 2020.

7. Exploiting Model Hierarchies, Sparsity and Low-Rank Structure of Large-scale Bayesian Computation (with Bui-Thanh and Scheichl), *SIAM Conference on Computational Science and Engineering*, Spokane, Washington, USA, 2019.

8. Multilevel and Multifidelity Bayesian Methods for Inverse Problems and Beyond (with Peherstorfer), *SIAM Conference on Uncertainty Quantification*, Garden Grove CA, USA, 2018.

9. Structure exploiting methods in large-scale Bayesian computation (with Bui-Thanh and Law), *Applied Inverse Problems Conference*, Hangzhou, China, 2017.

10. Advances in MCMC and Related Sampling Methods for Large-Scale Inverse Problems (with Tan Bui-Thanh and Youssef Marzouk), *SIAM Conference on Computational Science and Engineering*, Atlanta, USA, 2017.

11. Low Rank and Sparse Structure in Large-scale Bayesian Computation (with Kody Law, Youssef Marzouk and Alessio Spantini), *SIAM Conference on Uncertainty Quantification*, Lausanne, Switzerland, 2016.

12. Numerical Bayesian Analysis (with Colin Fox and Richard Norton), *SIAM Conference on Uncertainty Quantification*, Lausanne, Switzerland, 2016.

13. Advances in MCMC and Related Sampling Methods for Large-scale Inverse Problems (with Tan Bui-Thanh and Youssef Marzouk), *International Congress on Industrial and Applied Mathematics*, Beijing, China, 2015.

14. Advances in Markov Chain Monte Carlo Methods for Large-scale Inverse Problems (with Kody Law and Youssef Marzouk), *SIAM Conference on Uncertainty Quantification*, Savannah, GA, USA, 2014.

15. Surrogate and Reduced Order Modeling for Statistical Inversion and Prediction (with Youssef Marzouk and Karen Willcox), *SIAM Conference on Uncertainty Quantification*, Savannah, GA, USA, 2014.

8 Invited Presentations

1. Intrinsic Subspaces of High-Dimensional Inverse Problems and Where to Find Them. *Joint Meeting of the NZMS, AustMS and AMS, 2024*, Auckland, New Zealand, December, 2024.

2. Tensor-Train Methods for Sequential State and Parameter Estimation in State-Space Models. *International Conference on Scientific Computation and Differential Equations*, Joint Meeting of the NZMS, AustMS and AMS, 2024, Auckland, New Zealand.December, 2024

3. Tensor-Train Methods for Sequential State and Parameter Estimation in State-Space Models. *Sydney Workshop on Mathematics of Data Science*, University of Sydney, Sydney, Australia, 04 – 06, December 2024.

4. Tensor-Train Methods for Sequential State and Parameter Estimation in State-Space Models. *The First MSU-BIT Conference on Tensor Methods in Mathematics and Data Science*, Shenzhen MSU-BIT, Shenzhen, China, 17 – 22, November, 2024.

5. Intrinsic Subspaces of High-Dimensional Inverse Problems and Where to Find Them. *Numerical Analysis Seminar*, Heidelberg University, 17 October, 2024.

6. From Matrix Interpolation to Tensorized High-Dimensional Random Variable Simulation with Applications to Bayesian Computation. *Digital twins for inverse problems in Earth science*, University of Sydney, Australia, 22 August, 2024.

7. Optimization-Based Samplers for Hierarchical Bayesian Inverse Problems. *Image X Institute*, Sydney, Australia, 6 August, 2024.

8. Tensor-Train Methods for Sequential State and Parameter Estimation in State-Space Models. *Digital twins for inverse problems in Earth science*, CIRM (International Centre Meetings Mathematics), France, 22 – 26 July, 2024.

9. Tensor-Train Methods for Sequential State and Parameter Estimation in State-Space Models. *International Conference on Scientific Computation and Differential Equations*, National University of Singapore, Singapore, July 15 – 19, 2024.

10. Intrinsic subspaces of high-dimensional inverse problems and where to find them. *Applied and Computational Math Seminar*, Southeast University, China, 11 June, 2024.

11. Intrinsic Subspaces of High-Dimensional Inverse Problems and Where to Find Them. *Applied Math Seminar*, Macquarie University, Australia, 23 May, 2024.

12. Scalable conditional transport maps using tensor trains. *The Annual Workshop on Optimisation, Metric Bounds, Approximation and Transversality (WOMBAT 2023)*, Sydney, Australia, 11 – 15 December 2023.

13. Scalable conditional transport maps using tensor trains. *67th Annual Meeting of the Australian Mathematical Society*, The University of Queensland, Brisbane, Australia, 5–8 December 2023.

14. DIRT: a self-reinforced Knothe–Rosenblatt method. *Computer Vision and Learning Seminar*, Heidelberg, Germany, 13 November, 2023.

15. Tensor-train methods for sequential state and parameter learning in state-space models. *International Congress on Industrial and Applied Mathematics (ICIAM) 2023*, Tokyo, Japan, August, 2023.

16. Sequential Bayesian filtering and parameter estimation using tensor trains. *Mathematical Foundations of Data Assimilation and Inverse Problems, Foundation of Computational Mathematics*, Paris, France, 12–21, June, 2023.

17. Self-reinforced Knothe-Rosenblatt rearrangements for high-dimensional stochastic computation . *9th Workshop on High-Dimensional Approximation (HDA2023)*, ANU, Canberra, Australia, February, 2023.

18. Intrinsic Subspaces of High-Dimensional Inverse Problems and Where to Find Them. *CUQI Seminar*, Technical University of Denmark, 11 November, 2022.

19. Intrinsic Subspaces of High-Dimensional Inverse Problems and Where to Find Them. *SIAM Conference on Mathematics of Data Science*, San Diego, CA, USA, September 26-30, 2022.

20. DIRT: a tensorised inverse Rosenblatt transport method. *Computational Uncertainty Quantification: Mathematical Foundations, Methodology & Data*, Erwin Schrödinger International Institute for Mathematics and Physics, Vienne, Austria, 2 May–24 June, 2022.

21. Multi-level optimization based Monte-Carlo samplers for large-scale inverse problems. *Computational Uncertainty Quantification: Mathematical Foundations, Methodology & Data*, Erwin Schrödinger International Institute for Mathematics and Physics, Vienne, Austria, 2 May–24 June, 2022.

22. DIRT: tensorised Rosenblatt transport for high-dimensional stochastic computation. *SIAM Conference on Uncertainty Quantification*, online, 12–15 April, 2022.

23. Optimization-based sampling approaches for hierarchical Bayesian inverse problems. *SIAM Conference on Imaging Science*, online, 21–25 March, 2022.

24. Tensorised Rosenblatt Transport for High-Dimensional Stochastic Computation. *Applied Math Seminar*, ShanghaiTech University, Shanghai, China, 18 October, 2021.

25. Tensorised Rosenblatt transport for high-dimensional stochastic computation. *SIAM Conference on Mathematical & Computational Issues in the Geosciences*, online, 21–24 June, 2021.

26. Tensorised Rosenblatt transport for high-dimensional stochastic computation. *SIAM Conference on Computational Science and Engineering*, online, 12–13 March, 2021.

27. Tensorised Rosenblatt Transport for High-Dimensional Stochastic Computation. *Workshop on Scientific Computing and Optimization*, Hong Kong, China, 12–13 December 2020.

28. Tensorised Rosenblatt Transport for High-Dimensional Stochastic Computation. *Applied Math Seminar*, National University of Singapore, Singapore, 14 October, 2020.

29. A Stein Variational Newton Method. *Institute of Natural Sciences Seminar*, Shanghai Jiaotong University, China, 8 January, 2020.

30. A Stein variational Newton method (plenary speaker). *IMS Applied Mathematics and Data Science Workshop*, Shanghai, China, 6–10 January, 2020.

31. Optimization-based sampling approaches for Bayesian inference (keynote speaker). *Uncertainty Quantification Workshop, MSI Special Year 2019 in Computational Mathematics*, Canberra, Australia, 25–29 November, 2019.

32. A Stein variational Newton method. *FMI Workshop on Inverse Problems and Uncertainty Quantification in Satellite Remote Sensing*, Helsinki, Finland, 8–12 Oct, 2019.

33. Advanced multi-level sampling methods for large-scale Bayesian inverse problems. *19th Copper Mountain Conference On Multigrid Methods*, Copper Mountain, Colorado, USA, 24–28 March, 2019.

34. A Stein variational Newton method. *RICAM workshop on Frontier Technologies for High-Dimensional Problems and Uncertainty Quantification*, Linz, Austria, 17–21 Dec, 2018.

35. Optimization-based sampling approaches for hierarchical Bayesian inference. *Algorithms and Applications of High Dimensional Approximation*, University of Bath, UK, 22 Nov–23 Nov, 2018.

36. Optimization-based sampling approaches for hierarchical Bayesian inference. *16th Annual Meeting of China Society for Industrial and Applied Mathematics*, Chengdu, China, 14–16 Sep, 2018.

37. Subspace acceleration for large-scale Bayesian inverse problems. *Bayesian Computation for High-Dimensional Statistical Models*, Institute for Mathematical Sciences, National University of Singapore, Singapore, 27 August–21 September, 2018.

38. Optimisation-based sampling approaches for hierarchical Bayesian inference. *Bayesian Computation for High-Dimensional Statistical Models*, Institute for Mathematical Sciences, National University of Singapore, Singapore, 27 August–21 September, 2018.

39. Subspace acceleration for large-scale Bayesian inverse problems. *On the Frontier of High-dimensional Computation*, MATRIX Institute, Creswick, Australia, 4–15 June, 2018.

40. Optimisation-based sampling approaches for hierarchical Bayesian inverse problems. *On the Frontier of High-dimensional Computation*, MATRIX Institute, Creswick, Australia, 4–15 June, 2018.

41. Subspace acceleration for large-scale Bayesian inverse problems (plenary speaker). *Computational Methods for Design and Control of Next-Generation Engineered Systems*, Singapore University of Technology and Design, Singapore, 30 May–1 June, 2018.

42. Subspace acceleration for large-scale Bayesian inverse problems. *International Conference on Uncertainty Quantification in Computational Fluid Dynamics*, Shanghai Jiaotong University, Shanghai, China, July 24–27, 2017.

43. Joint model and parameter reduction for large-scale Bayesian inversion. *SIAM Conference on Computational Science and Engineering*, Atlanta, USA, February 27–March 3, 2017.

44. Joint model and parameter reduction for large-scale Bayesian inversion. *Workshop on Computational and Mathematical Foundations for Big Data Analytics*, Queensland University of Technology, Brisbane, Australia, July 25–26, 2016.

45. Subspace acceleration strategies for sampling on function space. *SIAM Conference on Uncertainty Quantification*, Lausanne, Switzerland, April 5–8, 2016.