

Jonathan H. Huggins

CONTACT INFORMATION	655 Huntington Avenue Building 2 Boston, MA 02115 USA	✉ jhuggins -at- mit -dot- edu 🌐 jhhuggins.org	
EDUCATION	Massachusetts Institute of Technology , Cambridge, MA USA Ph.D., Computer Science. Advisor: Tamara Broderick S.M., Computer Science. Advisor: Joshua B. Tenenbaum		2014 - 2018 2012 - 2014
	Columbia University, Columbia College , New York, NY USA B.A., Mathematics. Advisors: Liam Paninski and Frank D. Wood		2008 - 2012
ACADEMIC EXPERIENCE	Harvard University, Department of Biostatistics , Boston, MA USA Postdoctoral Research Fellow. Advisor: Jeffrey Miller		2018 -
	Microsoft Research New England , Cambridge, MA USA Research Intern. Advisor: Lester Mackey		2017
PROFESSIONAL EXPERIENCE	Google Inc. , New York, NY USA Summer Engineering Intern		2012
	MITRE Corp. , Bedford, MA USA Technical Co-op		2007 - 2009
HONORS AND AWARDS	ISBA@NeurIPS travel award (2016) DoD National Defense Science and Engineering Graduate Fellowship (2013-2015) NSF Graduate Research Fellowship (2013) (<i>declined for DoD NDSEG</i>) Hertz Fellowship Finalist (2013) Summa Cum Laude, Columbia University (2012) Phi Beta Kappa (2011) Rabi Scholar, Columbia College (2008-2012) Intel Science Talent Search Finalist (2008)		
PREPRINTS	<ul style="list-style-type: none">• M. Shiffman, W. Stephenson, G. Schiebinger, J. H. Huggins, T. C. Campbell, A. Regev & T. Broderick. Reconstructing probabilistic trees of cellular differentiation from single-cell RNA-seq data. <i>arXiv:1811.11790 [q-bio.QM]</i>.• J. H. Huggins, M. Kasprzak, T. C. Campbell & T. Broderick. Practical bounds on the error of Bayesian posterior approximations: A nonasymptotic approach. <i>arXiv:1809.09505 [stat.TH]</i>.		
PUBLICATIONS	16. T. C. Campbell*, J. H. Huggins *, J. P. How & T. Broderick (To appear). Truncated Random Measures. <i>Bernoulli</i> .		
	15. J. H. Huggins , T. C. Campbell, M. Kasprzak & T. Broderick (2019). Scalable Gaussian process inference with finite-data mean and variance guarantees. In <i>Proc. of the 21st International Conference on Artificial Intelligence and Statistics</i> .		
	14. R. Agrawal, T. C. Campbell, J. H. Huggins & T. Broderick (2019). Data-dependent compression of random features for large-scale kernel approximation. In <i>Proc. of the 21st International Conference on Artificial Intelligence and Statistics</i> .		

13. **J. H. Huggins*** & D. M. Roy* (2019). Sequential Monte Carlo as approximate sampling: bounds, adaptive resampling via ∞ -ESS, and an application to particle Gibbs. *Bernoulli* 25(1), 584–622.
12. **J. H. Huggins*** & L. Mackey* (2018). Random feature Stein discrepancies. In *Proc. of the 32nd Annual Conference on Neural Information Processing Systems*.
11. **J. H. Huggins**, R. P. Adams & T. Broderick (2017). PASS-GLM: polynomial approximate sufficient statistics for scalable Bayesian GLM inference. In *Proc. of the 31st Annual Conference on Neural Information Processing Systems*.
▷ Selected for spotlight presentation (top 22% of accepted papers)
10. **J. H. Huggins*** & J. Zou* (2017). Quantifying the Accuracy of Approximate Diffusions and Markov Chains. In *Proc. of the 19th International Conference on Artificial Intelligence and Statistics*.
9. **J. H. Huggins**, T. C. Campbell & T. Broderick (2016). Coresets for Scalable Bayesian Logistic Regression. In *Proc. of the 30th Annual Conference on Neural Information Processing Systems*.
8. **J. H. Huggins** & J. B. Tenenbaum (2015). Risk and Regret of Hierarchical Bayesian Learners. In *Proc. of the 32nd International Conference on Machine Learning*.
7. **J. H. Huggins***, A. Saeedi*, K. Narasimhan* & V. K. Mansinghka (2015). JUMP-Means: Small-Variance Asymptotics for Markov Jump Processes. In *Proc. of the 32nd International Conference on Machine Learning*.
6. **J. H. Huggins** & C. Rudin (2014). A statistical learning theory framework for supervised pattern discovery. In *Proc. of SIAM International Conference on Data Mining*.
5. A. Pakman, **J. H. Huggins**, C. Smith & L. Paninski (2014). Fast state-space methods for inferring dendritic synaptic connectivity. *Journal of Computational Neuroscience* 36(3), 415–443.
4. E. Pnevmatikakis, K. Rahnama Rad, **J. H. Huggins** & L. Paninski (2014). Fast low-SNR Kalman filtering and forward-backward smoothing via a low-rank perturbative approach. *Journal of Computational and Graphical Statistics* 23(2), 316–339.
3. **J. H. Huggins** & L. Paninski (2012). Optimal experimental design for sampling voltage on dendritic trees in the low-SNR regime. *Journal of Computational Neuroscience* 32(2), 347–66.
2. M. Vilain, **J. H. Huggins** & B. Wellner (2009). Sources of performance in CRF transfer training: a business name-tagging case study. In *Proc. of Recent Advances in Natural Language Processing 2009*.
1. M. Vilain, **J. H. Huggins** & B. Wellner (2009). A simple feature-copying approach to long-distance dependencies. In *Proc. of the 13th Conference on Computational Natural Language Learning 2009*.

★ = contributed equally

WORKSHOP
PAPERS

3. B. Trippe, **J. H. Huggins** & T. Broderick (2018). Fast Bayesian Inference in GLMs with Low Rank Data Approximations. In *Symposium on Advances in Approximate Bayesian Inference*.
2. **J. H. Huggins**, L. Masoero, L. Mackey & T. Broderick (2017). Generic finite approximations for practical Bayesian nonparametrics. In *NeurIPS 2017 Workshop on Advances in Approximate*

Bayesian Inference.

1. M. Shiffman, W. Stephenson, G. Schiebinger, T. C. Campbell, **J. H. Huggins**, A. Regev & T. Broderick (2017). Probabilistic reconstruction of cellular differentiation trees from single-cell RNA-seq data. In *NeurIPS 2017 Workshop on Machine Learning in Computational Biology*.

MISCELLANEA

2. **J. H. Huggins**, A. Saeedi & M. J. Johnson (2014). Detailed Derivations of Small-variance Asymptotics for some Hierarchical Bayesian Nonparametric Models. *arXiv:1501.00052 [stat.ML]*.

1. **J. H. Huggins** & F. Wood (2014). Infinite structured hidden semi-Markov models. *arXiv:1407.0044 [stat.ME]*.

INVITED TALKS

Upcoming

Bristol University, Bristol, UK October 2019

Broad Institute of MIT and Harvard, Cambridge, MA February 2019

Northeastern University, Boston, MA February 2019

Previous

Boston University, Boston, MA January 2019
Scalable, Reliably Accurate Bayesian Inference via Approximate Likelihoods and Random Features

SPA 2018, Gothenburg, Sweden June 2018
Finite-dimensional Approximations of Completely Random Measures

Boston Bayesian Meetup, Boston, MA April 2018

Schlumberger Doll Research, Cambridge, MA April 2018
Scaling Bayesian Inference by Constructing Approximating Exponential Families

Raytheon BBN Technologies, Cambridge, MA February 2018
Scaling Bayesian Inference: Theoretical Foundations and Practical Methods

CONTRIBUTED TALKS

ISBA World Meeting, Edinburgh, Scotland June 2018
Scaling Bayesian Inference by Constructing Approximating Exponential Families

BNP 2017, Paris, France June 2017
Truncated Random Measures

PROFESSIONAL SERVICE

Area Chair: Advances in Neural Information Processing Systems (NeurIPS)
Journal Reviewer: PLoS One, Journal of Machine Learning Research
Conference Reviewer: Advances in Neural Information Processing Systems (NeurIPS), International Conference on Machine Learning (ICML), Artificial Intelligence and Statistics (AISTATS)

TEACHING

Massachusetts Institute of Technology

- Teaching Assistant, 6.862 Applied Machine Learning (Graduate-level) 2017
- Guest Lecturer, 6.438 Fundamentals of Probability 2016
- Teaching Assistant, 6.867 Machine Learning (Graduate-level) 2016

Columbia University

- Teaching Assistant, Data Structures 2011

- Guest Lecturer, Statistical Analysis of Neural Data (Graduate-level)

2011