MIT Economics

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Doctoral Studies

Massachusetts Institute of Technology (MIT)
PhD, Economics & Statistics, Expected completion June 2023
DISSERTATION: "Essays on Econometrics, Causal Inference, & Machine Learning"

DISSERTATION COMMITTEE AND REFERENCES

Professor Whitney K. Newey
MIT Department of Economics
77 Massachusetts Avenue, E52-520
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Professor Anna Mikusheva
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Professor Alberto Abadie
MIT Department of Economics and
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77 Massachusetts Avenue, E52-546
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Professor Victor Chernozhukov
MIT Department of Economics and
Institute for Data, Systems, & Society
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Prior Education

University College London — 2017
MSc, Computational Statistics & Machine Learning
Distinction

The London School of Economics & Political Science — 2016
MSc, Econometrics & Mathematical Economics
Distinction

Yale University — 2015
BA, Economics & Mathematics
Magna Cum Laude, Distinction in the Major

Citizenship USA

Gender Male

FIELDS

Primary Fields: Econometrics, Causal Inference, Machine Learning

Secondary Field: Labor Economics

TEACHING EXPERIENCE

Econometrics (graduate) Teaching Assistant to Profs. Alberto Abadie & Whitney Newey	2023
Research & Communication in Economics (undergraduate) Teaching Assistant to Prof. Sara Ellison	2023
Intro to Stat in Economics (undergraduate; 7.0/7.0 median rating) Teaching Assistant to Prof. Alberto Abadie	2021
Intro to Stat in Economics (undergraduate; 7.0/7.0 median rating) Teaching Assistant to Profs. Alberto Abadie & Whitney Newey	2019
Nonlinear Econometrics (graduate; 6.0/7.0 median rating) Teaching Assistant to Profs. Alberto Abadie & Whitney Newey	2019

RELEVANT POSITIONS

Causality Research Fellow, Simons Institute for the Theory of Computing, UC Berkeley	2022
Machine Learning Research Intern to Prof. Vasilis Syrgkanis, Microsoft Research New England	2020
Research Assistant to Profs. Glenn Ellison & Parag Pathak, NBER	2016
Risk Intern, Earnest, San Francisco CA	2015
Summer Intern, The President's Council of Economic Advisers, The White House (Obama Administration)	2014
Financial Literacy Teacher, New Haven Reads, New Haven CT	2013-14
Tobin Research Assistant to Prof. Costas Meghir, Yale	2013

FELLOWSHIPS, HONORS, AND AWARDS

Simons-Berkeley Research Fellowship	2022
MIT Prize for Open Data, Runner Up	2022
ICML Outstanding Reviewer Award	2022
NeurIPS Outstanding Reviewer Award	2021
Jerry A. Hausman Graduate Fellowship	2018, 20
MIT Presidential Fellowship	2017
Marshall Scholarship	2015
Phi Beta Kappa	2015
Senator John Heinz Government Service Fellowship	2014
Henry James TenEyck Oratory Prize, 2nd	2014
E. Francis Riggs Humanities Prize, 2nd	2013

PROFESSIONAL ACTIVITIES

Referee:
Econometrica, *Review of Economic Studies*, *Review of Economics & Statistics*, *Journal of Econometrics*; *Journal of the Royal Statistical Society: Series B*, *Journal of the American Statistical Association: Theory & Methods*, *Biometrika*, *Journal of Nonparametric Statistics*; *Journal of Machine Learning Research*, *NeurIPS*, *ICML*, *ICLR*.

Service:

Participant, Working Session on Implications of New Data Privacy Protection Methods for Economic Research, ASSA	2023
Co-coordinator, Statistical Theory for Causal Estimation Working Group, Simons Institute	2022
Mentor, Application Assistance and Mentoring Program, MIT	2020-22
Mentor, Undergraduate Research Opportunity Program, MIT	2020-22
Program Committee, Workshop on Machine Learning Meets Econometrics, NeurIPS	2021
Program Committee, Workshop on Causal Sequential Decisions, NeurIPS	2021
Session Chair, Econometric Society World Congress	2020
Co-coordinator, High Dimensional Probability & Statistics Reading Group, MIT	2018-19
Rossborough Fellow, Women's Center, Yale	2013-14
Peer Liaison, Asian American Cultural Center, Yale	2012

Presentations:

ASSA Annual Meeting	2023
Online Causal Inference Seminar	2022
Conference on Computational and Methodological Statistics	2022
INFORMS Annual Meeting, Oral Presentation	2022
American Causal Inference Conference, Oral Presentation	2022
California Econometrics Conference, Oral Presentation	2022
Berkeley Econometrics Seminar	2022
Berkeley Causal Inference Research Group	2022
Berkeley Biostatistics Seminar	2022
Simons Workshop on Algorithmic Aspects of Causal Inference	2022
ASSA Annual Meeting (co-author)	2022
Wharton Statistics (Tchetgen Tchetgen Lab)	2021
ETH Zurich Causality Reading Group	2020
Microsoft Research New England	2020
Econometric Society World Congress	2020
ASSA Annual Meeting (co-author)	2020
NeurIPS Oral Presentation	2019
NeurIPS Workshop on Causal ML, Spotlight (co-author)	2019
MIT LIDS Causal Inference Tutorial	2019

PUBLICATIONS

"Automatic debiased machine learning of causal and structural effects" (with Victor Chernozhukov and Whitney K. Newey) *Econometrica*, 2022.

"A simple and general debiased machine learning theorem with finite sample guarantees" (with Victor Chernozhukov and Whitney K. Newey) *Biometrika*, 2022.

“Debiased machine learning of global and local parameters using regularized Riesz representers” (with Victor Chernozhukov and Whitney K. Newey) *The Econometrics Journal*, 2022.

“Kernel instrumental variable regression” (first author; with Maneesh Sahani and Arthur Gretton) *NeurIPS*, 2019 (Oral presentation; 0.5% acceptance rate).

RESEARCH PAPERS

“Causal inference with corrupted data: Measurement error, missing values, discretization, and differential privacy” (Job Market Paper) (with Anish Agarwal)
arXiv: 2107.02780, 2021. Extended abstract in *NeurIPS Workshop on Machine Learning Meets Econometrics*, 2021.

The US Census Bureau will deliberately corrupt data sets derived from the 2020 US Census in an effort to maintain privacy, suggesting a painful trade-off between the privacy of respondents and the precision of economic analysis. To investigate whether this trade-off is inevitable, we formulate a semiparametric model of causal inference with high dimensional corrupted data. We propose a procedure for data cleaning, estimation, and inference with data cleaning-adjusted confidence intervals. We prove consistency, Gaussian approximation, and semiparametric efficiency by finite sample arguments, with a rate of $n^{-1/2}$ for semiparametric estimands that degrades gracefully for nonparametric estimands. Our key assumption is that the true covariates are approximately low rank, which we interpret as approximate repeated measurements and validate in the Census. In our analysis, we provide nonasymptotic theoretical contributions to matrix completion, statistical learning, and semiparametric statistics. Calibrated simulations verify the coverage of our data cleaning-adjusted confidence intervals and demonstrate the relevance of our results for 2020 Census data.

“Kernel methods for unobserved confounding: Negative controls, proxies, and instruments”
arXiv: 2012.10315, 2020. Revised & resubmitted to *Journal of the American Statistical Association: Theory & Methods.*

Negative control is a strategy for learning the causal relationship between treatment and outcome in the presence of unmeasured confounding. The treatment effect can nonetheless be identified if two auxiliary variables are available: a negative control treatment (which has no effect on the actual outcome), and a negative control outcome (which is not affected by the actual treatment). These auxiliary variables can also be viewed as proxies for a traditional set of control variables, and they bear resemblance to instrumental variables. I propose a family of algorithms based on kernel ridge regression for learning nonparametric treatment effects with negative controls. Examples include dose response curves, dose response curves with distribution shift, and heterogeneous treatment effects. Data may be discrete or continuous, and low, high, or infinite dimensional. I prove uniform consistency and provide finite sample rates of convergence. I estimate the dose response curve of cigarette smoking on infant birth weight adjusting for unobserved confounding due to household income, using a data set of singleton births in the state of Pennsylvania between 1989 and 1991.

"Double robustness for complier parameters and a semiparametric test for complier characteristics"
(with Liyang Sun)
arXiv: 1909.05244, 2019. Extended abstract in *NeurIPS Workshop on Causal Machine Learning*, 2019 (Spotlight presentation). Submitted.

We propose a semiparametric test to evaluate (i) whether different instruments induce subpopulations of compliers with the same observable characteristics on average, and (ii) whether compliers have observable characteristics that are the same as the full population on average. The test is a flexible robustness check for the external validity of instruments. We use it to reinterpret the difference in LATE estimates that Angrist and Evans (1998) obtain when using different instrumental variables. To justify the test, we characterize the doubly robust moment for Abadie (2003)'s class of complier parameters, and we analyze a machine learning update to κ weighting.

"Kernel methods for causal functions: Dose, heterogeneous, and incremental response curves"
(first author; with Liyuan Xu and Arthur Gretton)
arXiv: 2010.04855, 2020. Extended abstract in *NeurIPS Workshop on Machine Learning for Economic Policy*, 2020. Submitted.

We propose estimators based on kernel ridge regression for nonparametric causal functions such as dose, heterogeneous, and incremental response curves. Treatment and covariates may be discrete or continuous in general spaces. Due to a decomposition property specific to the RKHS, our estimators have simple closed form solutions. We prove uniform consistency with improved finite sample rates, via original analysis of generalized kernel ridge regression. We extend our main results to counterfactual distributions and to causal functions identified by front and back door criteria. In nonlinear simulations with many covariates, we achieve state-of-the-art performance.

"Kernel methods for multistage causal inference: Mediation analysis and dynamic treatment effects"
(first author; with Liyuan Xu and Arthur Gretton)
arXiv: 2111.03950, 2021. Extended abstract in *NeurIPS Workshop on Causal Sequential Decisions*, 2021. Submitted.

We propose simple estimators for mediation analysis and dynamic treatment effects over short horizons based on kernel ridge regression. We study both nonparametric response curves and semiparametric treatment effects, allowing treatments, mediators, and covariates to be continuous or discrete in general spaces. Our key innovation is a new RKHS technique called sequential mean embedding, which facilitates the construction of simple estimators for complex causal estimands, including new estimands without existing alternatives. In particular, we propose machine learning estimators of dynamic dose response curves and dynamic counterfactual distributions without restrictive linearity, Markov, or no-effect-modification assumptions. Our simple estimators preserve the generality of classic identification while also achieving nonasymptotic uniform rates for causal functions and semiparametric efficiency for causal scalars. In nonlinear simulations with many covariates, we demonstrate state-of-the-art performance. We estimate mediated and dynamic response curves of the US Job Corps program for disadvantaged youth, and share a data set that may serve as a benchmark in future work.

"A finite sample theorem for longitudinal causal inference with machine learning: Long term, dynamic, and mediated effects"
arXiv: 2112.14249, 2021.

I construct and justify confidence intervals for longitudinal causal parameters estimated with machine learning. Longitudinal parameters include long term, dynamic, and mediated effects. I provide a nonasymptotic theorem for any longitudinal causal parameter in a general class, estimated with any machine learning algorithm that satisfies a few simple conditions. The main result encompasses local parameters defined for specific demographics as well as proximal parameters defined in the presence of unobserved confounding. I prove consistency, Gaussian approximation, and semiparametric efficiency. The rate of Gaussian approximation is $n^{-1/2}$ for global parameters, and it degrades gracefully for local parameters. I articulate a simple set of conditions to translate mean square rates into statistical inference, and verify that they hold for adversarial estimators over generic function spaces. A key feature of the main result is a new multiple robustness to ill posedness for proximal causal inference in longitudinal settings. Of independent interest, I provide what appears to be the first mean square rate for nested nonparametric instrumental variable regression.

"Adversarial estimation of Riesz representers"
(with Victor Chernozhukov, Whitney K. Newey, and Vasilis Syrgkanis)
arXiv: 2101.00009, 2020. Extended abstract in *ICML Workshop on New Frontiers in Adversarial Machine Learning*, 2022.

We provide an adversarial approach to estimating Riesz representers of linear functionals within arbitrary function spaces. We prove oracle inequalities based on the localized Rademacher complexity of the function space used to approximate the Riesz representer and the approximation error. These inequalities imply fast finite sample mean square error rates for many function spaces of interest, such as high dimensional sparse linear functions, neural networks and reproducing kernel Hilbert spaces. Our approach offers a new way of estimating Riesz representers with a plethora of recently introduced machine learning techniques. We show how our estimator can be used in the context of debiasing structural and causal parameters in semiparametric models, for automated orthogonalization of moment equations, and for estimating the stochastic discount factor in the context of asset pricing.

"Automatic debiased machine learning for dynamic treatment effects and general nested functionals"
(with Victor Chernozhukov, Whitney K. Newey, and Vasilis Syrgkanis)
arXiv: 2203.13887, 2022.

We extend the idea of automated debiased machine learning to the dynamic treatment regime and more generally to nested functionals. We show that the multiply robust formula for the dynamic treatment regime with discrete treatments can be restated in terms of a recursive Riesz representer characterization of nested mean regressions. We then apply a recursive Riesz representer estimation learning algorithm that estimates debiasing corrections without the need to characterize how the correction terms look—such as for instance, products of inverse probability weighting terms, as is done in prior work on doubly robust estimation in the dynamic regime. Our approach defines a sequence of loss minimization problems, whose minimizers are the multipliers of the debiasing correction, hence circumventing the need for solving auxiliary propensity models and directly optimizing for the mean square error of the target debiasing correction. We provide further applications of our approach to estimation of dynamic discrete choice models and estimation of long term effects with surrogates.

RESEARCH IN PROGRESS

"Debiased kernel methods" *arXiv: 2102.11076*, 2021.

"Kernel methods for attrition bias" *arXiv: 2111.05277*, 2021.

"Kernel methods for long term causal inference" *arXiv: 2201.05139*, 2022.