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Kohei Yata

Address: Department of Economics
Yale University
New Haven, CT 06520-8268

Telephone: (+1) 475-243-8183

E-mail: kohei.yata@yale.edu

Web page: https://koheiyata.com

Citizenship: Japan, F-1 Visa

Fields of Concentration:
Primary Field: Econometrics
Secondary Fields: Applied Microeconometrics, Machine Learning, Marketing

Desired Teaching:
Econometrics
Applied Econometrics
Machine Learning

Comprehensive Examinations Completed:
2018 (Oral): Econometrics, Industrial Organization
2017 (Written): Microeconomics, Macroeconomics

Dissertation Title: *Econometric Methods for Policy Choice and Policy Evaluation*

Committee:
Professor Yuichi Kitamura (Chair)
Professor Timothy B. Armstrong
Professor Yusuke Narita

Expected Completion Date: May 2022

Degrees:
Ph.D., Economics, Yale University, 2022 (expected)
M.Phil., Economics, Yale University, 2019
M.A., Economics, Yale University, 2018
M.A., Economics, University of Tokyo, 2016
B.A., Economics, University of Tokyo, 2014

Fellowships, Honors and Awards:
University Dissertation Fellowship, Yale University, 2020-2021

Besen and Dublirer Families Endowed Fellowship, 2017-2019
University Fellowship, Yale University, 2016-2020
Cowles Foundation Fellowship, 2016-2020
Research Fellowship for Young Scientists (DC1), Japan Society for Promotion of Sciences, 2016

Research Grants:

Kikawada Foundation Research Grant, 2016-2018
Research Grant for Japan Society for Promotion of Sciences Research Fellows, 2016

Teaching Experience:

Spring 2020, Teaching Fellow to Prof. Min Seong Kim, Econometrics (Undergraduate), Yale College
Spring 2019, Teaching Fellow to Prof. Yuichi Kitamura, Econometrics (Undergraduate), Yale College
Fall 2018, Teaching Fellow to Prof. Nicholas Ryan, Introduction to Econometrics and Data Analysis I (Undergraduate), Yale College
Spring 2015, Teaching Assistant to Prof. Katsumi Shimotsu, Econometrics (Graduate School of Public Policy), University of Tokyo
Winter 2014, Teaching Assistant to Prof. Akihiko Matsui, Microeconomics (Undergraduate), University of Tokyo

Research and Work Experience:

Visiting Scholar, Institute of Economic Research, Hitotsubashi University, July-September 2020
Research Intern, QuantCo, Inc., June-July 2019
Research Assistant to Prof. Edward Vytlacil, Yale University, June-August 2018
Research Assistant to Prof. Yusuke Narita, Yale University, June 2017-May 2018
Research Assistant to Prof. Masahiro Okuno-Fujiwara, Musashino University, December 2014-March 2016
Research Assistant to Prof. Yasuyuki Sawada, Research Institute of Economy, Trade and Industry, Oct 2013-March 2014

Publications:

"Debiased Off-Policy Evaluation for Recommendation Systems" (2021) with Yusuke Narita and Shota Yasui, *Proceedings of the 15th ACM Conference on Recommender Systems*, 372-379.

"Efficient Counterfactual Learning from Bandit Feedback" (2019) with Yusuke Narita and Shota Yasui, *Proceedings of the AAAI Conference on Artificial Intelligence*, 33(01), 4634-4641.

Working Papers:

"Optimal Decision Rules Under Partial Identification" (November 2021), *Job Market Paper*

"Algorithm is Experiment: Machine Learning, Market Design, and Policy Eligibility Rules" with Yusuke Narita (October 2021)

- Best Paper Award at the ACM conference on Equity and Access in Algorithms, Mechanisms, and Optimization (EAAMO 2021)

Work In Progress:

"When to Target Customers? Retention Management Using Dynamic Off-Policy Policy Learning" with Kosuke Uetake

Seminar and Conference Presentations:

2021: Happy Hour Seminar, Bayesian Causal Inference for Real World Interactive Systems Workshop (KDD 2021), Machine Learning for Consumers and Markets Workshop (KDD 2021), Reinforcement Learning for Real Life Workshop (ICML 2021), Annual Meetings of the Society of Labor Economists (SOLE), North American Winter Meeting of the Econometric Society

2020: European Winter Meeting of the Econometric Society, World Congress of the Econometric Society

2019: AAAI Conference on Artificial Intelligence

2018: RIKEN AIP Open Seminar

2016: Japanese Economic Association Spring Meeting

Languages:

Japanese (native), English (fluent)

References:

Prof. Yuichi Kitamura
Yale University
Department of Economics
New Haven, CT 06520
PO Box 208281
Phone: (+1) 203-432-3699
yuichi.kitamura@yale.edu

Prof. Timothy B. Armstrong
University of Southern California
Department of Economics
Los Angeles, CA 90089
Phone: (+1) 213-740-3511
timothy.armstrong@usc.edu

Prof. Yusuke Narita
Yale University
Department of Economics
New Haven, CT 06520
Phone: (+1) 857-999-1570
yusuke.narita@yale.edu

Dissertation Abstract

Optimal Decision Rules Under Partial Identification [Job Market Paper]

I propose an optimal way of using data to make policy decisions. This method is especially useful when social welfare (e.g., the population mean of an outcome) under each counterfactual policy is only partially determined by observed data. For example, a standard Regression Discontinuity (RD) design only estimates the impact of the policy treatment on the marginally treated. Therefore, without restrictive assumptions such as constant treatment effects, whether or not to offer the treatment to the whole population is ambiguous. My approach adopts a formulation based on partial identification and allows one to make optimal decisions without such ad hoc assumptions.

Specifically, I construct an optimal procedure by solving a class of statistical decision problems. The setup is as follows. Using a finite sample, we must decide between two alternative policies (e.g., the status quo and a new policy) to maximize welfare. The data-generating model and welfare under each policy depend on an unknown, possibly infinite-dimensional parameter, such as counterfactual outcome functions. The parameter only needs to lie in a known, convex, and symmetric (with respect to the origin) set, potentially leading to partial identification of the welfare effects. An example of such restrictions is the smoothness of counterfactual outcome functions.

As the main theoretical result, I obtain a finite-sample decision rule (i.e., a function that maps data to a decision) that is optimal under the minimax regret criterion. That is, it minimizes the worst-case expected welfare loss among all possible decision rules. Importantly, it is simple and thus easy to compute, yet achieves optimality among every decision rule; no ad hoc functional-form restrictions are imposed on the class of decision rules. I compare the optimal rule with a decision rule based on a mean-squared-error-optimal estimator. I show that the latter is not necessarily optimal under the minimax regret criterion. A special case of my result is an optimal decision rule for deciding whether or not to change a policy eligibility cutoff in an RD setup. To the best of my knowledge, no prior results about optimal decisions exist for this problem even under restrictive assumptions such as constant treatment effects.

I illustrate my approach using data from the BRIGHT school construction program in Burkina Faso (Kazianga, Levy, Linden, and Sloan, 2013). The program allocates schools to villages based on whether a score summarizing village characteristics is above or below a specific cutoff. I consider whether or not to expand the program and build schools in more villages. When cost data are available, in addition to outcome data, my approach can be used to obtain the most cost-effective decision. Under reasonable restrictions on the smoothness of counterfactual outcome functions, the optimal decision rule implies that expanding the program is not cost-effective.

Algorithm is Experiment: Machine Learning, Market Design, and Policy Eligibility Rules, with Yusuke Narita

Algorithms produce a growing portion of decisions and recommendations both in policy and in business. Such algorithmic decisions are conditionally quasi-randomly assigned since the algorithms make decisions based only on observable input covariates. We use this observation to develop a treatment-effect estimator for a class of stochastic and deterministic decision-making algorithms. Our proposed method exploits local variation in the algorithm's decision, adjusting for the imbalance in covariates between groups who receive different decisions from the algorithm. Our estimator is shown to be consistent and asymptotically normal for well-defined causal effects. A key special case of our estimator is a multidimensional Regression Discontinuity design. We apply our estimator to evaluate the effect of the Coronavirus Aid, Relief, and Economic Security (CARES) Act, where hundreds of billions of dollars worth of relief funding were allocated to hospitals via an algorithmic rule. Our estimates suggest that the relief funding has little effect on COVID-19-related hospital activity levels. Naive OLS and IV estimates without appropriate control for the algorithm's input covariates exhibit substantial selection bias.

When to Target Customers? Retention Management Using Dynamic Off-Policy Policy Learning, with Kosuke Uetake

We develop and estimate a dynamic targeting strategy for managing customer retention. Working with a Japanese online platform, we first implement a large-scale randomized experiment, in which coupons are sent to first-time buyers at different random timings. The experimental data allow us to estimate the optimal dynamic targeting policy using off-policy policy learning methods. We extend existing methods by explicitly considering constraints such as budget constraints. The preliminary results show that our policies produce a greater rate of customer retention than the random allocation policy used in the experiment at the same cost level. We also find that it is possible to achieve almost the same retention rate as the optimal unconstrained policy with a much lower cost.