Interaction Effects and Causal Heterogeneity

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Interaction Effects and Causal Heterogeneity

- Heterogenous treatment effects:

  1. Moderation
     - How do treatment effects vary across individuals?
     - Who benefits from (or is harmed by) the treatment?
     - Interaction between treatment and pre-treatment covariates
  2. Causal interaction
     - What aspects of a treatment are responsible for causal effects?
     - What combination of treatments is most efficacious?
     - Interaction between treatment variables
  3. Individualized treatment regimes
     - What combination of treatments is optimal for a given individual?

Randomized Evaluation of Job Training Program

- National Supported Work (NSW) Program (LaLonde 1986)
- Randomized evaluation; 297 treated units, 425 control units
- Two motivations for estimating heterogenous treatment effects
  1. Who benefit most (or harmed most by) from the program?
  2. Generalizing experimental results to a target population
- Target population: Panel Study of Income Dynamics with an over-sample of low-income individuals
- 45 Pre-treatment covariates X_i:
  - age, race, education, employment in 1975, etc.
  - all two-way interactions
- Outcome: Did the earnings increase after the program?
- Estimate the conditional average treatment effect:

$$\mathbb{E}(Y_i(1) - Y_i(0) \mid X_i)$$

The Proposed Methodology

- Binary outcome: $Y_i \in \{-1, 1\}$
- Optimal classification: Support vector machine
- Variable selection: Lasso

- The objective function:

$$(\hat{\beta}, \hat{\gamma}) \;=\; \underset{(\beta,\gamma)}{\operatorname{argmin}} \sum_i w_i \cdot \left|1 - Y_i \cdot (\mu + \beta^\top T_i X_i + \gamma^\top X_i)\right|_+^2 + \lambda_\beta \sum_j |\beta_j| + \lambda_\gamma \sum_j |\gamma_j|$$

where w_i is the weight and $|x|_+ = \max(x, 0)$ is the hinge-loss

- ATE estimates:
  1. NSW: 6.22 percentage points
  2. PSID: 5.16 percentage points

Those who Benefit Most from the Program

1. Single non-hispanics with low education and some earnings

effect	age	educ.	high school	race	married	earnings	PSID
47	31	4	No	White	No	10700	1.38
45	31	4	No	Black	No	4020	0.97

2. Unemployed blacks with high school degree

effect	age	educ.	high school	race	married	earnings	PSID
40	28	15	Yes	Black	No	0	0.89
39	30	14	Yes	Black	Yes	0	1.28
37	22	16	Yes	Black	No	0	0.98
35	34	13	Yes	Black	Yes	0	1.43

Those who are Harmed Most by the Program

1. Single hispanics with no college education and some earnings

effect	age	educ.	high school	race	married	earnings	PSID
−22	27	12	Yes	Hisp	No	24300	0.95
−21	36	12	Yes	Hisp	No	11500	1.12
−21	36	11	No	Hisp	No	3060	0.88
−21	34	11	No	Hisp	No	4640	0.89
−17	29	10	No	Hisp	No	8850	0.83
−16	29	9	No	Hisp	No	16300	0.89

2. Single whites with high school degree and some earnings

effect	age	educ.	high school	race	married	earnings	PSID
−18	31	12	Yes	White	No	2610	1.22
−17	31	12	Yes	White	No	495	1.13
−16	29	12	Yes	White	No	12200	1.44

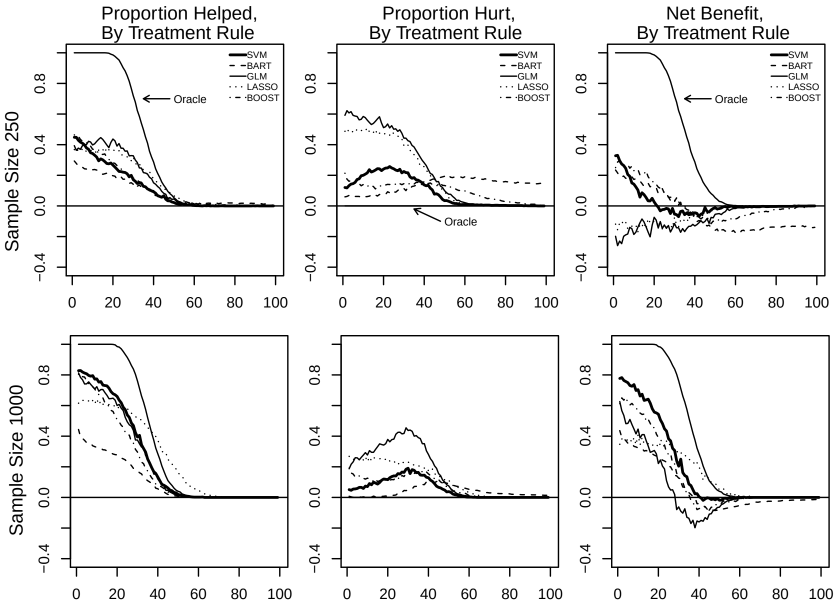
A Simulation Study: Set-up

- Twenty controls, each interacted with a single treatment
- 15 continuous (multvariate normal), 5 binary

- Maximum and minimum effect sizes: 4 and -2.5 percentage points
- Remainder between ± 1 percentage points
- Sample sizes from 250 and 5,000
- Other methods: BART, bayes GLM, lasso, Boosting

- Classification payoffs: $\frac{1}{2} \times \mathbf{1}\{\hat{\tau}(X_i) > 0\} \times \mathrm{sgn}\{\tau(X_i)\}$
  1. 0.5: the treated observation is helped by the treatment
  2. -0.5: the treated observation is harmed by the treatment
  3. 0: untreated observations

A Simulation Study: Results



Two Interpretations of Causal Interaction

1. Conditional effect interpretation:
   - Does the effect of one treatment change as we vary the value of another treatment?
   - Does the effect of being black change depending on whether an applicant is male or female?
   - Useful for testing moderation among treatments
2. Interactive effect interpretation:
   - Does a combination of treatments induce an *additional effect* beyond the sum of separate effects attributable to each treatment?
   - Does being a black female induce an additional effect beyond the effect of being black and that of being female?
   - Useful for finding efficacious treatment combinations in high dimension

An Illustration in the 2 × 2 Case

- Two binary treatments: A and B
- Potential outcomes: $Y(a,b)$ where $a, b \in \{0,1\}$
- Conditional effect interpretation:

$$\underbrace{[Y(1,1) - Y(0,1)]}_{\text{effect of } A \text{ when } B=1} - \underbrace{[Y(1,0) - Y(0,0)]}_{\text{effect of } A \text{ when } B=0}$$

- Interactive effect interpretation:

$$\underbrace{[Y(1,1) - Y(0,0)]}_{\text{effect of } A \text{ and } B} - \underbrace{[Y(1,0) - Y(0,0)]}_{\text{effect of } A \text{ when } B=0} - \underbrace{[Y(0,1) - Y(0,0)]}_{\text{effect of } B \text{ when } A=0}$$

- The same quantity but two different interpretations
- The interactive interpretation requires the specification of the baseline condition: $(A,B) = (0,0)$ in this example

Causal Interaction in High Dimension

- In the 2 × 2 case, computing all four average potential outcomes gives a complete picture
- The dimensionality rapidly increases as the number of levels and treatments increase
- A motivating application: Conjoint analysis (Hainmueller *et al.* 2014)
  - survey experiments to measure immigration preferences
  - a representative sample of 1,396 American adults
  - `gender`^{2}, `education`^{7}, `origin`^{10}, `experience`^{4}, `plan`^{4}, `language`^{4}, `profession`^{11}, `application reason`^{3}, `prior trips`^{5}
  - Over 1 million treatment combinations
  - What combinations of profiles characterize (un)preferred immigrants?
- We focus on the interactive interpretation in high dimension

Difficulty of the Conventional Approach

- Lack of invariance to the baseline condition
- Inference depends on the choice of baseline condition
- 3×2 example:
  - Treatment $A \in \{a_0, a_1, a_2\}$ and Treatment $B \in \{b_0, b_1, b_2\}$
  - Regression model with the baseline condition (a_0, b_0):

$$\mathbb{E}(Y \mid A, B) \quad = \quad 1 + a_1^* + a_2^* + b_2^* + a_1^* b_2^* + 2a_2^* b_2^* + 3a_2^* b_1^*$$

  - Interaction effect for (a_2, b_2) $>$ Interaction effect for (a_1, b_2)
  - Another equivalent model with the baseline condition (a_0, b_1):

$$\mathbb{E}(Y \mid A, B) \quad = \quad 1 + a_1^* + 4a_2^* + b_2^* + a_1^* b_2^* - a_2^* b_2^* - 3a_2^* b_0^*$$

  - Interaction effect for (a_2, b_2) $<$ Interaction effect for (a_1, b_2)
  - Interaction effect for (a_2, b_1) is zero under the second model
  - All interaction effects with at least one baseline value are zero

The Contributions of the Paper

1. Standard treatment interaction effects suffer from the lack of order and interval invariance to the choice of baseline condition
2. Propose the marginal treatment interaction effect that is invariant
3. Derive the identification condition and estimation strategy for this new quantity
4. Generalize these results to the K-way causal interaction
5. Illustrate the methods with the immigration survey experiment

Two-way Causal Interaction

- Two factorial treatments:

$$\begin{aligned} A &\in \mathcal{A} = \{a_0, a_1, \ldots, a_{D_A-1}\} \\ B &\in \mathcal{B} = \{b_0, b_1, \ldots, b_{D_B-1}\} \end{aligned}$$

- Assumption: Full factorial design
  1. Randomization of treatment assignment

$$\{Y(a_\ell, b_m)\}_{a_\ell \in \mathcal{A}, b_m \in \mathcal{B}} \perp\!\!\!\perp \{A, B\}$$

  2. Non-zero probability for all treatment combination

$$\Pr(A = a_\ell, B = b_m) > 0 \quad \text{for all } a_\ell \in \mathcal{A} \quad \text{and} \quad b_m \in \mathcal{B}$$

- Fractional factorial design not allowed
  1. Use a small non-zero assignment probability
  2. Focus on a subsample
  3. Combine treatments

Non-Interaction Effects of Interest

1. Average Treatment Combination Effect (ATCE):
   - Average effect of treatment combination $(A, B) = (a_\ell, b_m)$ relative to the baseline condition $(A, B) = (a_0, b_0)$

     $$\tau(a_\ell, b_m; a_0, b_0) \quad \equiv \quad \mathbb{E}\{Y(a_\ell, b_m) - Y(a_0, b_0)\}$$

   - Which treatment combination is most efficacious?

2. Average Marginal Treatment Effect (AMTE; Hainmueller et al. 2014):
   - Average effect of treatment $A = a_\ell$ relative to the baseline condition $A = a_0$ averaging over the other treatment B

     $$\psi(a_\ell, a_0) \quad \equiv \quad \int_{\mathcal{B}} \mathbb{E}\{Y(a_\ell, B) - Y(a_0, B)\} dF(B)$$

   - Which treatment is effective on average?

The Conventional Approach to Causal Interaction

- Average Treatment Interaction Effect (ATIE):

$$\xi(a_\ell, b_m; a_0, b_0) \equiv \mathbb{E}\{Y(a_\ell, b_m) - Y(a_0, b_m) - Y(a_\ell, b_0) + Y(a_0, b_0)\}$$

- Conditional effect interpretation:

$$\underbrace{\mathbb{E}\{Y(a_\ell, b_m) - Y(a_0, b_m)\}}_{\text{Effect of } A = a_\ell \text{ when } B = b_m} - \underbrace{\mathbb{E}\{Y(a_\ell, b_0) - Y(a_0, b_0)\}}_{\text{Effect of } A = a_\ell \text{ when } B = b_0}$$

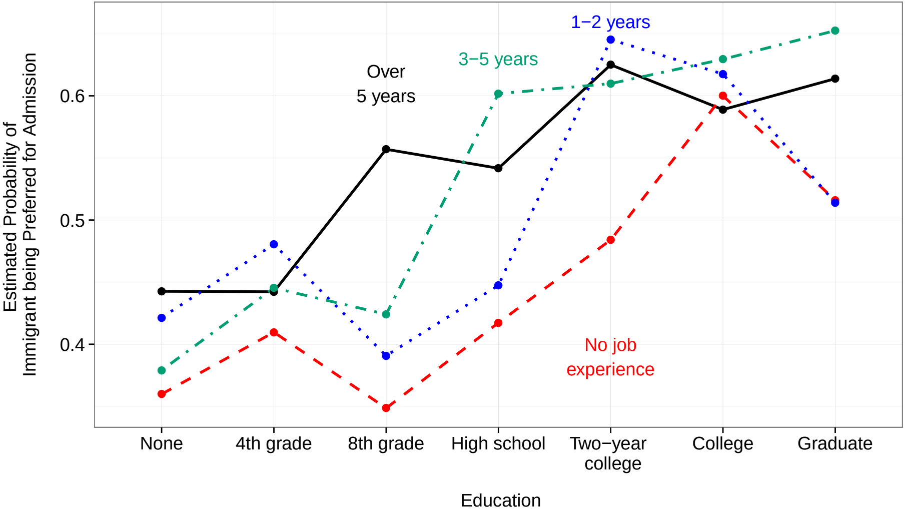
- Interactive effect interpretation:

$$\underbrace{\tau(a_\ell, b_m; a_0, b_0)}_{\text{ATCE}} - \underbrace{\mathbb{E}\{Y(a_\ell, b_0) - Y(a_0, b_0)\}}_{\text{Effect of } A = a_\ell \text{ when } B = b_0} - \underbrace{\mathbb{E}\{Y(a_0, b_m) - Y(a_0, b_0)\}}_{\text{Effect of } B = b_m \text{ when } A = a_0}$$

- Estimation: Linear regression with interaction terms

Ineffectiveness of Interaction Plot in High Dimension

Problem: it does not plot interaction effects themselves



Estimated Average Treatment Interaction Effect (ATIE)

				Education			
Job experience	None	4th grade	8th grade	High school	Two-year college	College	Graduate
None	0 (baseline)	0	0	0	0	0	0
1–2 years	0	0.009 (0.063)	−0.019 (0.063)	−0.032 (0.063)	0.100 (0.064)	−0.044 (0.064)	−0.064 (0.063)
3–5 years	0	0.016 (0.063)	0.056 (0.064)	0.165 (0.064)	0.107 (0.064)	0.010 (0.065)	0.117 (0.063)
$>$ 5 years	0	−0.050 (0.064)	0.126 (0.064)	0.042 (0.063)	0.058 (0.064)	−0.094 (0.064)	0.015 (0.064)

The Effects of Changing the Baseline Condition

	Education						
Job experience	None	4th grade	8th grade	High school	Two-year college	College	Graduate
None	0.015 (0.064)	0.065 (0.062)	−0.111 (0.064)	−0.027 (0.061)	−0.043 (0.063)	0.109 (0.063)	0
1–2 years	0.078 (0.064)	0.138 (0.062)	−0.066 (0.062)	0.006 (0.061)	0.120 (0.062)	0.129 (0.062)	0
3–5 years	−0.102 (0.062)	−0.036 (0.062)	−0.172 (0.063)	0.021 (0.062)	−0.054 (0.061)	0.002 (0.062)	0
>5 years	0	0	0	0	0	0	0 (baseline)

Lack of Invariance to the Baseline Condition

- Comparison between two ATIEs should not be affected by the choice of baseline conditions
- We prove that the ATIEs are neither interval or order invariant

- Interval invariance:

$$\begin{aligned} & \xi(a_\ell, b_m; a_0, b_0) \; - \; \xi(a_{\ell'}, b_{m'}; a_0, b_0) \\ = \; & \xi(a_\ell, b_m; a_{\tilde{\ell}}, b_{\tilde{m}}) \; - \; \xi(a_{\ell'}, b_{m'}; a_{\tilde{\ell}}, b_{\tilde{m}}), \end{aligned}$$

- Order invariance:

$$\begin{aligned} & \xi(a_\ell, b_m; a_0, b_0) \; \geq \; \xi(a_{\ell'}, b_{m'}; a_0, b_0) \\ \Longleftrightarrow \; & \xi(a_\ell, b_m; a_{\tilde{\ell}}, b_{\tilde{m}}) \; \geq \; \xi(a_{\ell'}, b_{m'}; a_{\tilde{\ell}}, b_{\tilde{m}}). \end{aligned}$$

The New Causal Interaction Effect

- Average Marginal Treatment Interaction Effect (AMTIE):

$$\begin{aligned} & \pi(a_\ell, b_m; a_0, b_0) \\ \equiv \quad & \underbrace{\tau(a_\ell, b_m; a_0, b_0)}_{\text{ATCE of } (A,B)=(a_\ell, b_m)} - \underbrace{\psi(a_\ell, a_0)}_{\text{AMTE of } A = a_\ell} - \underbrace{\psi(b_m, b_0)}_{\text{AMTE of } B = b_m} \end{aligned}$$

- Interactive effect interpretation: additional effect induced by $A = a_\ell$ and $B = b_m$ together beyond the separate effect of $A = a_\ell$ and that of $B = b_m$

- We prove that the AMTIEs are both interval and order invariant

- The AMTIEs do depend on the distribution of treatment assignment
  1. specified by one's experimental design
  2. motivated by the target population

The Relationships between the ATIE and the AMTIE

1. The AMTIE is a linear function of the ATIEs:

$$\begin{aligned}\pi(a_\ell, b_m; a_0, b_0) &= \xi(a_\ell, b_m; a_0, b_0) - \sum_{a \in \mathcal{A}} \Pr(A_i = a)\, \xi(a, b_m; a_0, b_0) \\ &\quad - \sum_{b \in \mathcal{B}} \Pr(B_i = b)\, \xi(a_\ell, b; a_0, b_0)\end{aligned}$$

2. The ATIE is also a linear function of the AMTIEs:

$$\xi(a_\ell, b_m; a_0, b_0) = \pi(a_\ell, b_m; a_0, b_0) - \pi(a_\ell, b_0; a_0, b_0) - \pi(a_0, b_m; a_0, b_0)$$

- Absence of causal interaction:
  All of the AMTIEs are zero if and only if all of the ATIEs are zero

- The AMTIEs can be estimated by first estimating the ATIEs

Higher-order Causal Interaction

- J factorial treatments: $\mathbf{T} = (T_1, \ldots, T_J)$
- Assumptions:
  1. Full factorial design
  $$Y(\mathbf{t}) \quad \perp\!\!\!\perp \quad \mathbf{T} \quad \text{and} \quad \Pr(\mathbf{T} = \mathbf{t}) \ > \ 0 \quad \text{for all } \mathbf{t}$$
  2. Independent treatment assignment
  $$T_j \quad \perp\!\!\!\perp \quad \mathbf{T}_{-j} \quad \text{for all } j$$
- Assumption 2 is not necessary for identification but considerably simplifies estimation

- We are interested in the K-way interaction where $K \leq J$
- We extend all the results for the 2-way interaction to this general case

Difficulty of Interpreting the Higher-order ATIE

- Generalize the 2-way ATIE by marginalizing the other treatments $\underline{\mathbf{T}}^{1:2}$

$$\xi_{1:2}(t_1, t_2; t_{01}, t_{02}) \equiv \int \mathbb{E}\left\{ Y(t_1, t_2, \underline{\mathbf{T}}^{1:2}) - Y(t_{01}, t_2, \underline{\mathbf{T}}^{1:2}) \right. \\ \left. - Y(t_1, t_{02}, \underline{\mathbf{T}}^{1:2}) + Y(t_{01}, t_{02}, \underline{\mathbf{T}}^{1:2}) \right\} dF(\underline{\mathbf{T}}^{1:2})$$

- In the literature, the 3-way ATIE is defined as

$$\begin{aligned} & \xi_{1:3}(t_1, t_2, t_3; t_{01}, t_{02}, t_{03}) \\ \equiv\ & \underbrace{\xi_{1:2}(t_1, t_2; t_{01}, t_{02} \mid T_3 = t_3)}_{\text{2-way ATIE when } T_3 = t_3} - \underbrace{\xi_{1:2}(t_1, t_2; t_{01}, t_{02} \mid T_3 = t_{03})}_{\text{2-way ATIE when } T_3 = t_{03}} \end{aligned}$$

- Higher-order ATIEs are similarly defined sequentially
- This representation is based on the conditional effect interpretation
- Problem: the conditional effect of conditional effects!

Interactive Interpretation of the Higher-order ATIE

- We show that the higher-order ATIE also has an interactive effect interpretation
- Example: 3-way ATIE, $\xi_{1:3}(t_1, t_2, t_3; t_{01}, t_{02}, t_{03})$, equals

$$\begin{aligned} & \underbrace{\tau_{1:3}(t_1, t_2, t_3; t_{01}, t_{02}, t_{03})}_{\text{ATCE}} \\ & - \Big\{\xi_{1:2}(t_1, t_2; t_{01}, t_{02} \mid T_3 = t_{03}) + \xi_{2:3}(t_2, t_3; t_{02}, t_{03} \mid T_1 = t_{01}) \\ & \qquad + \xi_{1,3}(t_1, t_3; t_{01}, t_{03} \mid T_2 = t_{02})\Big\} \quad \text{sum of 2-way conditional ATIEs} \\ & - \Big\{\tau_1(t_1, t_{02}, t_{03}; t_{01}, t_{02}, t_{03}) + \tau_2(t_{01}, t_2, t_{03}; t_{01}, t_{02}, t_{03}) \\ & \qquad + \tau_3(t_{01}, t_{02}, t_3; t_{01}, t_{02}, t_{03})\Big\} \quad \text{sum of (1-way) ATCEs} \end{aligned}$$

- Problems:
  1. Lower-order *conditional* ATIEs rather than lower-order ATIEs are used
  2. K-way ATCE $\neq$ sum of all K-way and lower-order ATIEs
  3. (We prove) Lack of invariance to the baseline conditions

The K-way Average Marginal Treatment Interaction Effect

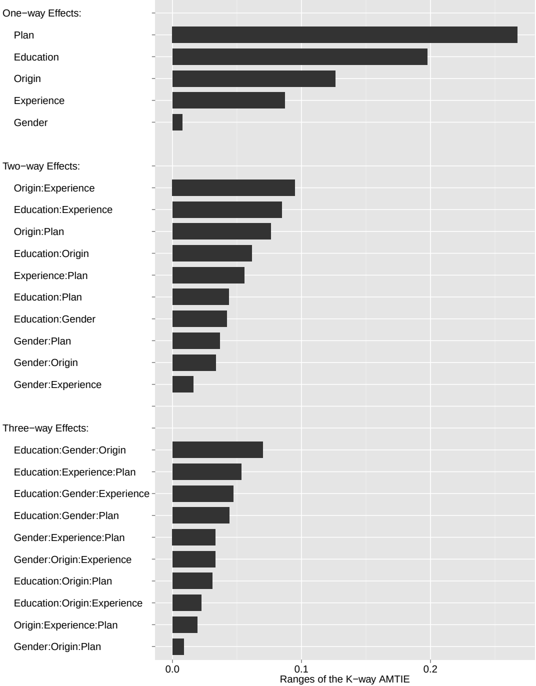
- Definition: the difference between the ATCE and the sum of lower-order AMTIEs
- Interactive effect interpretation
- Example: 3-way AMTIE, $\pi_{1:3}(t_1, t_2, t_3; t_{01}, t_{02}, t_{03})$, equals

$$\underbrace{\tau_{1:3}(t_1, t_2, t_3; t_{01}, t_{02}, t_{03})}_{\text{ATCE}}$$
$$- \underbrace{\left\{\pi_{1:2}(t_1, t_2; t_{01}, t_{02}) + \pi_{2:3}(t_2, t_3; t_{02}, t_{03}) + \pi_{1,3}(t_1, t_3; t_{01}, t_{03})\right\}}_{\text{sum of 2-way AMTIEs}}$$
$$- \underbrace{\left\{\psi(t_1; t_{01}) + \psi(t_2; t_{02}) + \psi(t_3; t_{03})\right\}}_{\text{sum of (1-way) AMTEs}}$$

- Properties:
  1. K-way ATCE $=$ the sum of all K-way and lower-order AMTIEs
  2. Interval and order invariance to the baseline condition
  3. Derive the relationships between the AMTIEs and ATIEs for any order

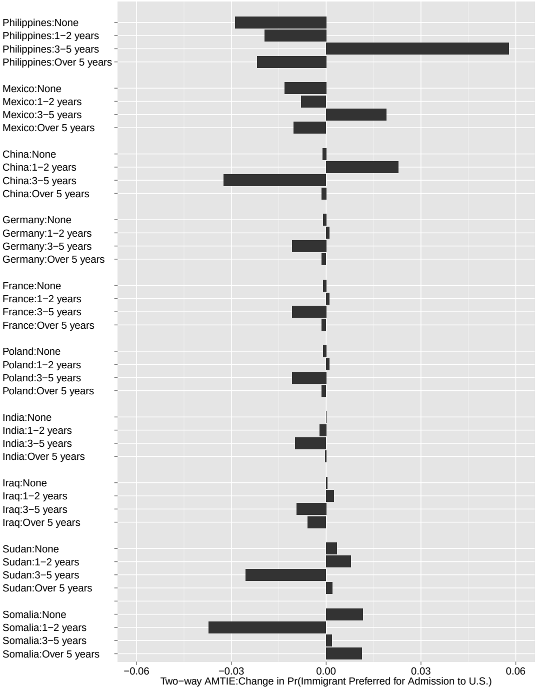
Empirical Analysis of the Immigration Survey Experiment

- 5 factors (`gender`^{2}, `education`^{7}, `origin`^{10}, `experience`^{4}, `plan`^{4})
  1. full factorial design assumption
  2. computational tractability
- Matched-pair conjoint analysis: randomly choose one profile
- Binary outcome: whether a profile is selected
- Model with one-way, two-way, and three-way interaction terms
- The "$p > n$" problem: $p = 1,575$ and $n = 1,396$
- Curse of dimensionality $\Longrightarrow$ sparcity assumption
- Support vector machine with a lasso constraint (Imai & Ratkovic, 2013)
- Over-identified model that includes baseline conditions
- 99 non-zero and $1,476$ zero coefficients
- Cross-validation for selecting a tuning parameter
- `FindIt: Finding heterogeneous treatment effects`



- Range of AMTIEs
- Variation within a factor interaction

- Sparcity-of-effects principle
- `gender` appears to play a significant role in three-way interactions



- `origin` × `experience` interaction
- Baseline: `India`, `None`
- Only relative magnitude matters

- Little interaction for European origin
- Similar pattern for `Mexico` and `Phillipines`
- Another similar pattern for `China`, `Sudan`, and `Somalia`

Decomposing the Average Treatment Combination Effect

- Two-way effect example (`origin` × `experience`):

$$\underbrace{\tau(\texttt{Somalia, 1-2 years; India, None})}_{-3.74}$$

$$= \underbrace{\psi(\texttt{Somalia}; \texttt{India})}_{-5.14} + \underbrace{\psi(\texttt{1} - \texttt{2years}; \texttt{None})}_{5.12} + \underbrace{\pi(\texttt{Somalia}, \texttt{1} - \texttt{2years}; \texttt{India}, \texttt{None})}_{-3.72}$$

- Three-way examples (`education` × `gender` × `origin`):

$$\underbrace{\tau(\texttt{Graduate}, \texttt{Male}, \texttt{India}; \texttt{Graduate}, \texttt{Female}, \texttt{India})}_{7.46}$$

$$= \underbrace{\psi(\texttt{Male}; \texttt{Female})}_{-0.77} + \underbrace{\pi(\texttt{Graduate}, \texttt{Male}; \texttt{Graduate}, \texttt{Female})}_{-0.34}$$

$$+ \underbrace{\pi(\texttt{Male}, \texttt{India}; \texttt{Female}, \texttt{India})}_{1.56} + \underbrace{\pi(\texttt{Graduate}, \texttt{Male}, \texttt{India}; \texttt{Graduate}, \texttt{Female}, \texttt{India})}_{7.01}$$

$$
\begin{aligned}
&\underbrace{\tau(\texttt{High school, Male, Germany; High school, Female, Germany})}_{-11.52} \\
= \ &\underbrace{\psi(\texttt{Male}; \texttt{Female})}_{-0.77} + \underbrace{\pi(\texttt{High school, Male; High school, Female})}_{-0.67} \\
+ \ &\underbrace{\pi(\texttt{Male}, \texttt{Germany}; \texttt{Female}, \texttt{Germany})}_{-3.34} \\
+ \ &\underbrace{\pi(\texttt{High school, Male,Germany; High school, Female,Germany})}_{-6.74}.
\end{aligned}
$$

Concluding Remarks

- Interaction effects play an essential role in causal heterogeneity
    1. moderation
    2. causal interaction
- Two interpretations of causal interaction
    1. conditional effect interpretation (problematic in high dimension)
    2. interactive effect interpretation
- Average Marginal Treatment Interaction Effect
    1. interactive effect in high-dimension
    2. invariant to baseline condition
    3. enables effect decomposition
- Estimation challenges in high dimension

References

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2. Egami, Naoki and Kosuke Imai. (2015). "Causal Interaction in High Dimension." Working Paper available at `http://imai.princeton.edu/research/int.html`

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