Causal Interaction in Factorial Experiments: Application to Conjoint Analysis

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Causal Heterogeneity and Interaction Effects

1. Moderation:
   - How does the effect of a treatment vary across individuals?
   - Interaction between the treatment variable and pre-treatment covariates

2. Causal interaction:
   - What combination of treatments is efficacious?
   - Interaction among multiple treatment variables

Conjoint Analysis

- Survey experiments with a factorial design
- Respondents evaluate several pairs of randomly selected profiles defined by multiple factors
- Frequently used for consumer research
- Social scientists use it to analyze multidimensional preferences
- Example: Immigration preference (Hopkins and Hainmueller 2014)
  - representative sample of 1,407 American adults
  - each respondent evaluates 5 pairs of immigrant profiles
  - `gender`^{2}, `education`^{7}, `origin`^{10}, `experience`^{4}, `plan`^{4}, `language`^{4}, `profession`^{11}, `application reason`^{3}, `prior trips`^{5}
  - What combinations of immigrant characteristics do Americans prefer?
  - High dimension: over 1 million treatment combinations
- Methodological challenges:
  - Many interaction effects $\rightsquigarrow$ false positives, difficulty of interpretation
  - Very few applied researchers study interaction

The Methodological Contributions

1. New causal estimand: Average Marginal Interaction Effect (AMIE)
    - relative magnitude does not depend on baseline condition
    - intuitive interpretation even for high dimension
    - estimation using ANOVA with weighted zero-sum constraints
    - regularization done directly on AMIEs

2. Comparison with the conventional interaction effect:
    - lack of invariance to the choice of baseline condition
    - difficulty of interpretation for higher-order interaction

Factorial Experiments with Two Treatments

- Two factorial treatments (e.g., gender and race):

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

- 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

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

Main Causal Estimands in Factorial Experiments

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

$$\tau_{AB}(a_\ell, b_m; a_0, b_0) \quad = \quad \mathbb{E}\{Y(a_\ell, b_m) - Y(a_0, b_0)\}$$

   - Effect of being Asian male

2. Average Marginal Effect (AME; Hainmueller *et al.* 2014; Dasgupta *et al.* 2015):
   - Average effect of treatment $A = a_\ell$ relative to the baseline condition $A = a_0$ averaging over the other treatment B

$$\psi_A(a_\ell, a_0) \quad = \quad \int \mathbb{E}\{Y(a_\ell, B) - Y(a_0, B)\} dF(B)$$

   - Effect of being male averaging over race

The New Causal Interaction Effect

- Average Marginal Interaction Effect (AMIE):

$$\pi_{AB}(a_\ell, b_m; a_0, b_0) = \underbrace{\tau_{AB}(a_\ell, b_m; a_0, b_0)}_{\text{ACE of } (a_\ell, b_m)} - \underbrace{\psi_A(a_\ell, a_0)}_{\text{AME of } a_\ell} - \underbrace{\psi_B(b_m, b_0)}_{\text{AME of } b_m}$$

- Interpretation: additional effect induced by $A = a_\ell$ and $B = b_m$ together beyond the separate effect of $A = a_\ell$ and that of $B = b_m$
- Additional effect of being Asian male beyond the sum of separate effects for being male and being Asian
- Invariance: *relative magnitude* of AMIE does not depend on the choice of baseline condition
- Generalizable to higher-order interaction
- ANOVA with direct regularization on AMEs and AMIEs

Conjoint Analysis of Ethnic Voting in Africa

- Ethnic voting and accountability (Carlson 2015, *World Politics*)
- Do voters prefer candidates of same ethnicity regardless of their prior performance? Do ethnicity and performance interact?

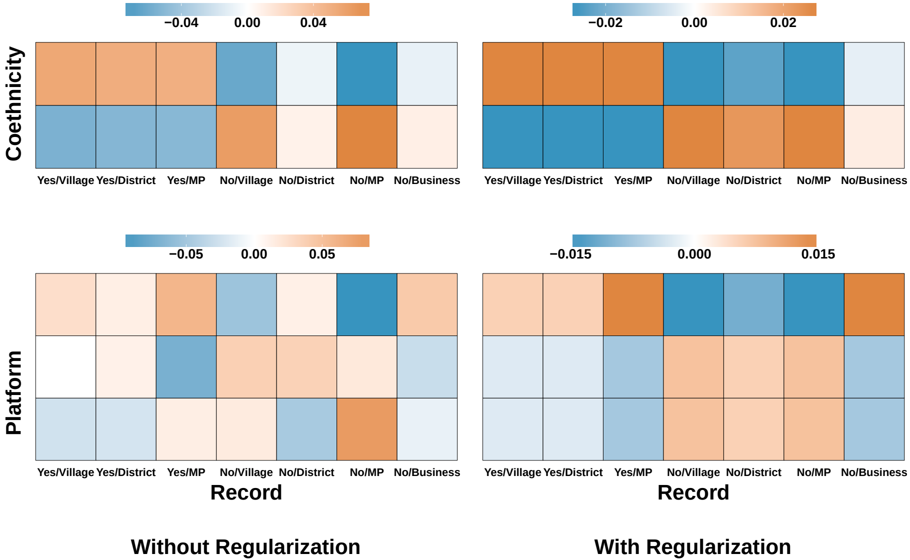
- Conjoint analysis in Uganda: 547 voters from 32 villages
- Each voter evaluates 3 pairs of hypothetical candidates
- 5 factors: `Coethnicity`^{2}, `Prior record`^{2}, `Prior office`^{4}, `Platform`^{3}, `Education`^{8}

Ranges of Estimated AMEs and AMIEs

	Range	Selection prob.
AME		
Record	0.122	1.00
Coethnicity	0.053	1.00
Platform	0.023	0.93
Degree	0.000	0.33
AMIE		
Coethnicity × Record	0.053	1.00
Record × Platform	0.030	0.92
Platform × Coethnic	0.008	0.64
Coethnicity × Degree	0.000	0.62
Platform × Degree	0.000	0.35
Record × Degree	0.000	0.09

- Factor selection probability based on bootstrap

Effect of Regularization on AMIEs



Concluding Remarks

- Interaction effects play an essential role in causal heterogeneity
  1. moderation
  2. causal interaction
- Randomized experiments with a factorial design
  1. useful for testing multiple treatments and their interactions
  2. social science applications: audit studies, conjoint analysis
  3. challenge: estimation and interpretation in high dimension
- Average Marginal Interaction Effect (AMIE)
  1. invariant to baseline condition
  2. straightforward interpretation even for high order interaction
  3. enables regularization through ANOVA
- Open questions:
  1. designing factorial experiments
  2. combining moderation and causal interaction

References

1. Egami, Naoki and Kosuke Imai. "Causal Interaction in Factorial Experiments: Application to Conjoint Analysis." *Journal of the American Statistical Association*, Forthcoming

2. Egami, Naoki, Marc Ratkovic, and Kosuke Imai. "FindIt: Finding Heterogeneous Treatment Effects." R package available at CRAN

Send comments and suggestions to

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