Adaptive Survey Design with Multiple Criteria: the American Community Survey

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Motivation for Adaptive Survey Design in the ACS

- Information collected in the ACS is critical
 - Largest continuous household survey in the US
 - Collects variety of information on household- and population-based topics
- Large overall sample sizes (3.5 million housing units per year)
 - Sequential multimode survey design to control costs
 - About 20% of ACS sample still ends up CAPI mode
- In the past (e.g., in 2022) data collection budgets were exhausted
 - Data collection was stopped for all CAPI cases no targeting
 - No chance to change the respondent set at time of work stoppage
 - Could exacerbate lead to nonresponse bias
- Goal: Create a Quality/Data-Driven Tool for Reallocating Effort



- Framework for Data Collection
 - Leverage tradeoffs
 - Min(budget) for a fixed level of data quality
 - Max(data quality) for a fixed budget
 - Balance resources and quality
 If we can save resources, willing to give up
 "some" data quality



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- Need predictive models to determine the impact of stopping cases
- Typically care about:
 - *Quality* summary statistic (variance inflation, MSE(item), CVs, etc.)
 - *Cost* cost-per-outcome (response, nonresponse, etc.) 2 viewpoints
 - "Cut Costs" other interviewer behavior stays the same, costs are reduced
 - "Reallocate Costs" shifts resources from stopped cases to retained cases
 - *Response Behavior* will a case actually respond?
 - Likely nonrespondents have impact on cost, but not on quality (vs baseline)
- Use model output to identify which cases to stop and their impact on quality



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• Juxtapose "importance" of case with "likelihood to respond"





Variance Inflation Factor Ratio of Alternate Strategy to Baseline Strategy













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- Goal 1: Need to reallocate 5% of budget *Need to accept a 1% variance inflation*
- Goal 2: Maximize resource shift for a 15% increase (or less) in variance inflation *You can obtain a 30% resource shift*
- Goal 3: Balance cost and variance inflation Find best tradeoff – minimum of product





Mathematical Optimization

• Formalize Idea

•
$$\varphi(\mathbf{A}) = \min_{A(i \in S)} \left(\left(\frac{\hat{C}^A | s^A, R^A}{\hat{C}^0 | s^0, R^0} \right) \left(\frac{\hat{V}^A | s^A, R^A}{\hat{V}^0 | s^0, R^0} \right) \right)$$

where *O* is the baseline strategy (normal data collection), and *A* is the alternate strategy (some set, *s*, of cases stopped)

- Response propensity model
- Balancing propensity model (for ranking)
- Cost model
- Variance inflation formula

$$r_{it} = p(R = 1 | \mathbf{X})$$

$$b_{it} = p(R = 1 | \mathbf{Z})$$

$$\hat{c}_i^o + \hat{c}_f^o$$

$$\hat{V}^A / \hat{V}^0$$

- Examples in the literature
 - National Survey of College Graduates minimize RMSE of key statistic (salary)
 - National Survey of Family Growth minimize the MSE of several key statistics
 - Dutch Labor Force Survey minimize mode effects in multimode survey



- ACS is cross-sectional, with no past response data for modeling
 - Need covariates for the balancing model
 - Characteristics related to outcomes of interest
 - Broad set of administrative data [MAF, Commercial Housing Data, IRS, SSA, Demographic Data from 2010/2020 Census, etc.]
 - Assign characteristics to sample units for the balancing model [sex, age, race/ethnicity, marital status, income, program participation flags, housing structure vars, etc.]



- ACS is Pseudo-longitudinal
 - Data collected for one panel is not released independently
 - 12 months of data combined into annual estimates (or 60 months for 5-yr)
 - Interventions we make could impact estimates for a long time
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 - Sample is spread across 12 months very small sample sizes
 - Can't run balancing propensity models at the tract level
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 - At least one occupied interview
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 - Retain enough sample to have two complete interviews
- This has led to a conservative stop work algorithm
 - Allowed us to develop models, code, evaluation metrics
 - Release version 1 of process for future improvements

What have we done so far?

- Development lasted from December 2022 June 2023
 - Data access and linkage
 - Model development
 - June 2023 end-to-end test stopped one case per state
- Implementation began July 2023
 - Stop Work Interventions Delivered for July, August, September, October
 - Midway through CAPI, carried out optimization procedures
 - Stopped 50% of the optimal number of cases for stop work (after restrictions)

What are we monitoring?

• Initial Monitoring

- Unweighted CAPI completion rate
- Mean balancing propensities
- CV(mean) balancing propensities
- R-Indicators (overall- and state-level)
- Future Monitoring
 - Attempts / hours on cases retained after stop work
- Longer-Term Monitoring
 - ACS 1-year estimates

Next Steps

- Consider different geographies for the balancing (quality) model
 - Urban-Rural? MSA? Something else?
 - How does changing the geography change stop work patterns?
- Improving cost/resource model
 - Add in additional covariates, geography, interviewer/workload characteristics
 - Incorporating mileage into the resource model
- Investigating impacts of resource reallocation
 - More hours on cases retained? More attempts?
 - Impact on response propensities for cases that are retained?
- Continuing to monitor outcomes
 - Completion rates, hours spent on cases, R-indicators, etc.

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