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Harnessing Paradata with Machine Learning to Inform Data Collection

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Introduction

- Cost of survey data collection is on the rise:
  - Survey response rates continue to decline despite more contact mode options (e.g., text, telephone).
  - The challenge is to identify cost and time-efficient ways to increase the likelihood of getting a response.
- Paradata contain a vast amount of information on when and how sampled persons are contacted and the outcome of each contact attempt.
- Can the analysis of paradata help inform the contact strategies and create efficiencies?

Related Work

- Paradata have been utilized to group households with similar contact history and outcomes (Durrant, G.B., Maslovskaya, O. and Smith, P.W., 2019).
- Propensity modeling informed by paradata predicts respondent likelihoods (Fang, Qixiang, et al., 2021).
- Studies used paradata to identify the optimal timing for reaching out in surveys (Shino, E., & McCarty, C. 2020).

Goals

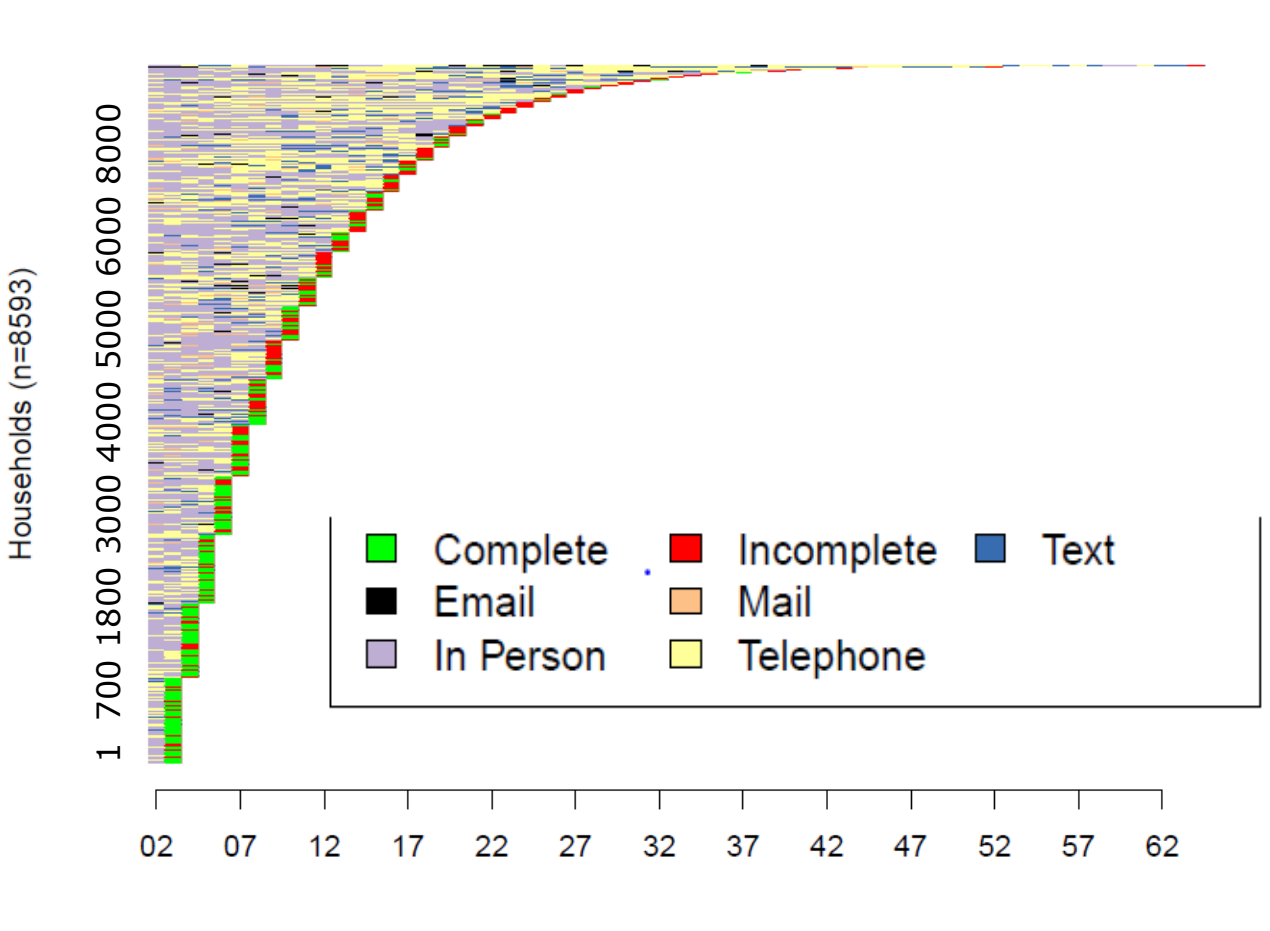
- This study aims to:
  - Understand how machine learning can be used to generate hypotheses from paradata to inform contact strategy.
  - Gather causal evidence for hypotheses.
  - Provide actionable insights for improving survey data collection.

Data

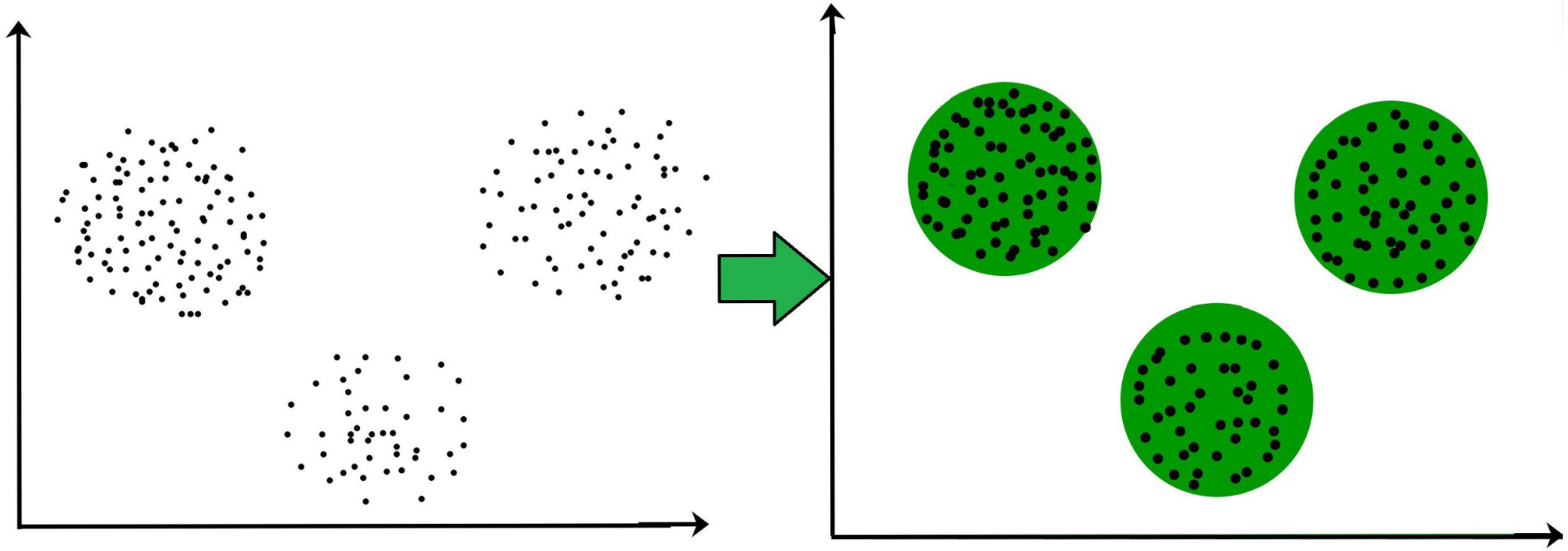
- Medical Expenditure Panel Survey (MEPS)
  - Nationally representative survey designed to explore healthcare use and expenditures in the U.S.
  - Conducted by Westat to support the Agency for Healthcare Research and Quality (AHRQ).
  - MEPS Household Component (MEPS-HC) collects data from a nationally representative sample of households, drawn from the National Health Interview Survey (NHIS).
  - High round 1 response rates are crucial to obtaining representative data.

Data

- MEPS Household Component Spring 2022 Round 1
  - 8,593 households with at least two contact attempts from 10,071 households
  - 4,707 complete, 3,886 incomplete (complete rate: 54.8%)
  - Paradata: Contact mode (In-Person, Telephone, Text, E-mail, or Mail) of each contact.



Unsupervised Machine Learning: Clustering



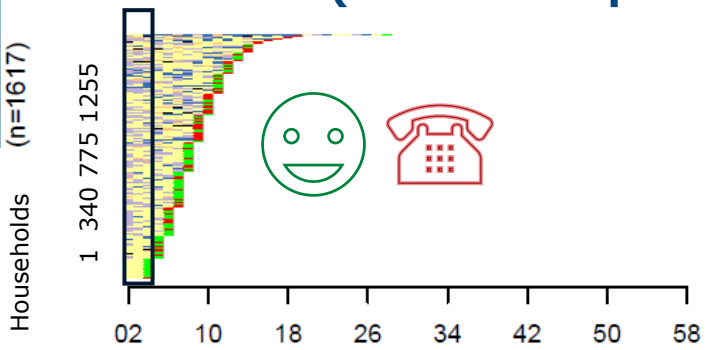
- Clustering algorithms automatically group similar observations.
- The measurement of similarities and number of groups are defined by humans.

Clustering Methods on Paradata

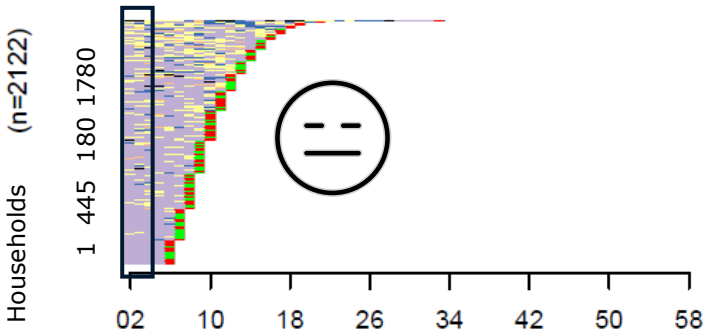
- **Observation**: Each household is represented by its contact mode sequence from contact 2 onward.
- **Similarity**: Calculated sequence distance using optimal matching (number of operation to transform sequences).
- **Clustering**: Partitioning Around Medoids algorithm

Clustering Results

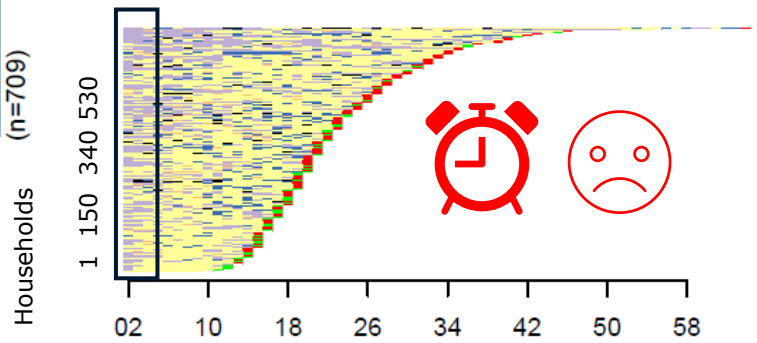
Cluster 1 (64.1% complete)



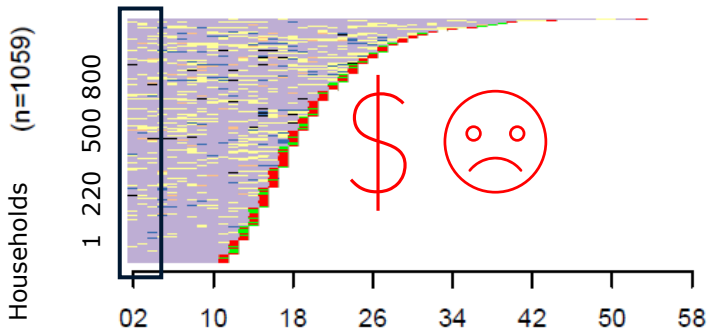
Cluster 2 (44.0% complete)



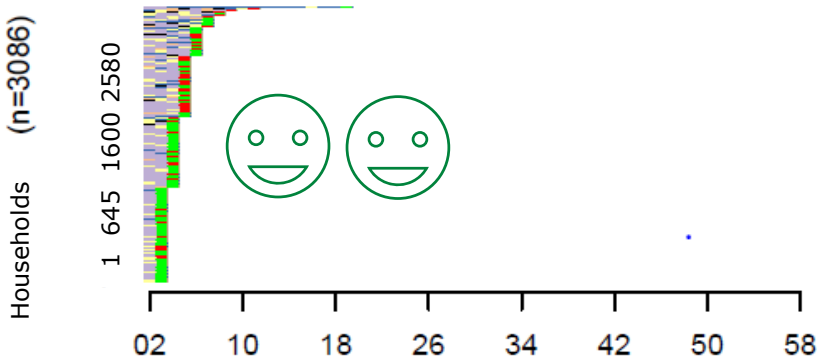
Cluster 3 (27.6% complete)



Cluster 4 (30.0% complete)



Cluster 5 (72.0% complete)



Clustering Results

		Cluster 1	Cluster 2	Cluster 3	Cluster 4	P
n		1617	2122	709	1059	
Contact 2-4 (%)	**Telephone**	**713 (44.1)**	**174 (8.2)**	**237 (33.4)**	**70 (6.6)**	<0.001
	In Person	**113 (7.0)**	**1255 (59.1)**	**181 (25.5)**	**705 (66.6)**	
	Mix	355 (22.0)	396 (18.7)	155 (21.9)	181 (17.1)	
	Other	309 (19.1)	297 (14.0)	136 (19.2)	103 (9.7)	
	Short	127 (7.9)	0 (0.0)	0 (0.0)	0 (0.0)	

Telephone: At least one telephone contact sequence during contact 2-4

In Person: Only in-person contact during contact 2-4

Mix: Mixed in-person and telephone contact during contact 2-4

Other: Other contact sequences during contact 2-4

Short: Contact sequence shorter than 4

Hypothesis

- **Hypothesis**:
  - Machine learning suggests that early telephone follow-ups after an initial in-person contact lead to a higher success rate.
- **Challenges in Testing Hypothesis:**
  - Households are not randomly assigned to contact modes.
  - Confounding factors such as household characteristics may make it difficult to determine the causal effects.

Target Trial Emulation

- **Question**: Is early telephone contact sequence associated with a higher success rate?
- **Cohort**: Households (Spring 2022, Round 1) with in-person first contact and telephone or in-person contacts during contacts 2-4
- **Exposure Group**:
  - 1. Treatment: Telephone sequence contact during contact 2-4.
  - 2. Control: Only in-person contact during contact 2-4.
- **Causal Inference**: Propensity score matching to mimic randomization.
- **Outcomes**: Response status during contacts 2-4 and days until completion.

Results

- **Propensity Score Matching**: Standardized differences are below 10%, indicating a well-balanced cohort.
- **Statistical Analysis**:
  - Telephone follow-ups were associated with increased likelihood of completion and positive response during contact 2-4.
  - The Kaplan-Meier analysis suggests that households with telephone follow-ups during contacts 2-4 complete the survey faster after contact 4.

Potential New Data Collection Strategies

- For households classified as likely to participate during the pre-round call period, prioritize telephone follow-ups after the initial in-person contact.
- For households without phone numbers, make efforts to match or obtain phone numbers before continuing with in-person contacts.
- Make appointment attempts during the pre-round call period.
- Ensure that face sheet information from NHIS data is available to guide the selection of the most effective interview mode for each household.

Conclusion and Future Directions

- **Conclusion**: Machine learning can improve data collection strategies by generating actionable insights from paradata-focused hypotheses.
- **Future Work**:
  - Gather information on the impact of the new strategies.
  - Generate and evaluate additional hypotheses.
  - Develop machine learning models for contact recommendations.

References

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Thank You!

Appendix

Clustering Methods on Paradata

- **Observation**: Each household is represented by its contact mode sequence from contact 2 onward.
- **Similarity**: Calculated sequence distance using optimal matching (numer of operation to transform sequences).
  - Substitution cost = 2
  - Insertion cost = 1
- **Clustering**: Partitioning Around Medoids algorithm

	Contact 2	Contact 3	Contact 4
Household 1	In-person	Telephone	In-person
Household 2	In-person	In-person	
Operation	None (0)	Substitution (2)	Insertion (1)

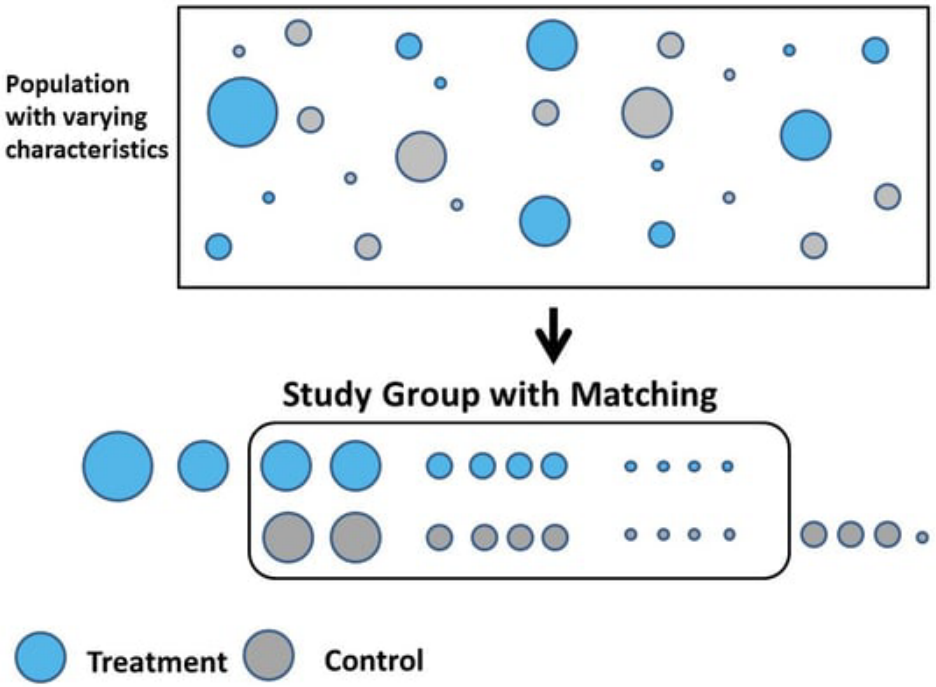
Propensity Score Matching

		Treatment (At least one telephone sequence contact during contact 2-4)	Control (Only in-person contact during contact 2-4)	Standard Difference (%)
n		764	764	
ACR	Likely	296 (38.74)	292 (38.22)	1.07
	Unlikely	77 (10.08)	75 (9.82)	0.87
	Mutual	58 (7.59)	61 (7.98)	-1.48
	Unknown	333 (43.59)	336 (43.98)	-0.79
Gender	Female	412 (53.93)	406 (53.14)	1.58
	Male	342 (44.76)	354 (45.16)	-0.79
	Unknown	10 (1.31)	13 (1.70)	-3.45
Race	White	532 (69.63)	537 (70.29)	-1.42
	Black	109 (14.27)	102 (13.35)	2.62
	Asian	61 (7.98)	57 (7.46)	1.93
	Multiple	11 (1.44)	10 (1.31)	1.10
	Other	1 (0.13)	0 (0.00)	3.62
	Unknown	65 (6.54)	64 (7.59)	-4.23
Age	=< 25	65 (8.51)	64 (8.38)	1.13
	26-54	532 (68.46)	519 (67.93)	0.47
	>=65	176 (23.04)	181 (23.69)	-1.55
House Size	1	211 (27.62)	223 (29.19)	-3.51
	2-4	476 (62.30)	472 (61.78)	1.08
	>= 5	77 (10.08)	69 (9.03)	3.48
Outcome01	Success	259 (33.90)	240 (31.41)	5.25
	Fail	524 (66.10)	505 (68.59)	-5.25

- All standard differences are below 10%.
- Means our analytic cohort is well-balanced across the potential confounders.
- Effectively mimicking randomization.

Causal Inference: Propensity Score Matching

- Propensity score matching (PSM) is a commonly used method to establish causality from observational studies.
- PSM pairs observations from different groups based on their likelihood of receiving treatment given a set of observed covariates.
- PSM emulates the randomization of treatment in observational studies by balancing the distribution of observed covariates between the treatment and control groups.



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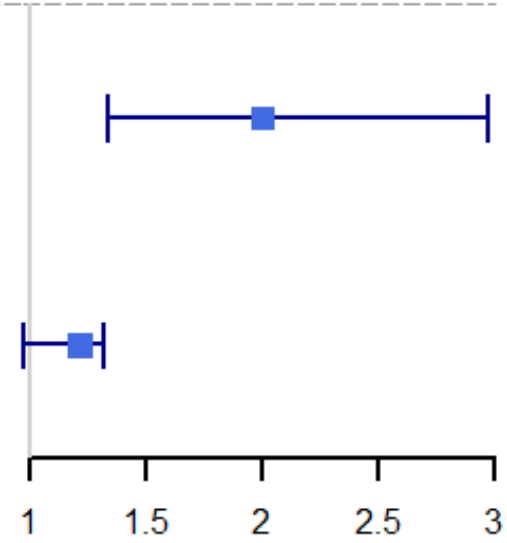
Outcome during contact 2-4

- A multinomial logistic regression model suggests:
  - Households with telephone follow-ups are 2 times more likely to complete during contact 2-4 as compared to those with in-person follow-ups.
  - Households with telephone follow-ups are 21% more likely to have a positive response during contact 2-4 as compared to those with in-person follow-ups.

Outcome	Treatment	Control	OR	P_value
Complete	79	46	2.00	<0.0001
Response	397	383	1.21	0.082



Days until the complete interview after contact 4

- The Kaplan-Meier curve suggests that households with telephone follow-ups during contacts 2-4 complete the survey faster after contact 4.