Increasing survey response rates and decreasing costs by combining numeric and text mining strategies on survey paradata

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Research Problem from American Community Survey (ACS) Operations

- Multi-dimensional problem
  - Declining response rates
  - Increasing collection costs
  - Exceeding respondent burden
- Multi-objective optimization problem with conflicting objectives
  - We present first steps to solve problem

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Physical Contact Attempts for Final Outcome

- Outcome code 201: Occupied } Completed
- Outcome code 218: Respondent refusal
- Outcome code 313: Respondent burden exceeded } Non-interview

- Average contact attempts:
  - 201: approx. 2.5 } 1.5M contact attempts (2017 + 2018)
  - 218: approx. 5
  - 313: approx. 7 } 600,000+ contact attempts (2017 + 2018)

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Costly contact attempts: Can we do better?

- **Research Question:**
  - Can we identify non-respondents based on first contact ONLY?
- **Answer:**
  - **We can identify 70-80% of non-respondent households**
- **Impact:**
  - Prioritize cases with higher probability of completion
  - Create adaptive design rules based on model results
- **How do we do it?**

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Current use of CHI in ACS

- CHI – Contact History Information
  - Paradata recorded by field rep when contact attempt is not successful in getting a response
- Burden score calculation based on CHI
  - Updated based on each contact attempt
- Burden score or CHI are not used to predict final response propensity (completion or refusal)

Research question and solution approach

- **Predict respondent refusal from first contact only -- using both numeric and textual information (structured and unstructured)**
  - CHI: Structured numeric information
  - Case Notes: free form text, unstructured
  - Combine and use CHI and Case Notes
- CHI based response propensity prediction model (new for ACS)
- Case Notes based response propensity model (new for Census)

Data merging: CHI with Case Notes

- 2017 and 2018 ACS CHI and Case Notes (focus of current analysis)
- Each CHI record was merged with zero-to-many Case Notes associated with that contact attempt
- Challenge: CHI and Case Notes captured on different systems
  - Merged on control number, date and timestamp
  - Timestamp does not match
  - Manually verified large (>400) samples to identify pattern of linkage
  - Custom linkage algorithm based on control number, date and proximity of timestamp between CHI and Case Notes

Data merging with Workload table

- First contact only model:
  - **CHI + Case Notes (First contact only) → ControlNumber → FINAL OUTCOME from Workload table**
  - (completed/refused when it happens in second or later contact)
- **Focus: Predict final outcome → based on first contact info**

Distribution of Outcome Codes for First Contact only model (2017 and 2018 data)

Outcome code	Definition	2017	2017 (percent)	2018	2018 (percent)
201	Occupied	225000	45%	205000	43%
218	Respondent refusal	36500	7%	45500	10%
313	Respondent burden exceeded	13000	3%	11000	2%
301	Vacant	95000	19%	88000	18%
501	Temporary occupied	2500	0.5%	2400	0.5%
203	Sufficient partial (occupied) - no follow-up	11500	2%	11500	2%

Predictive Model Setup

- **Predict:** Final outcome
  - 201 (completed) vs 218 (refused)
  - 201 (completed) vs 313 (burden exceeded)
- Prediction based on information from 1st contact only (personal or telephone)
- **Predictors:**
  - **Model 1:** CHI only
  - **Model 2:** Case Notes only (textual data)
  - **Model 3:** ALL CHI and Case Notes
  - **Model 4 variations**: Different CHI and Case Notes variables (based on variable importance)
    - Dimensionality reduction based on chi-square selection: all features (~10,000), best 6000 features, best 4000, best 2000.

Data undersampling used for modeling

- Models run: 201 vs 218, and 201 vs 313
- "Rare" occurrence of 218 (≤ 10%) and 313 (< 5%)
  - Undersampling needed for data for modeling

Undersampled data used for modeling						
	2017			2018		
Undersampling ratio:	**50-50**	**40-60**	**30-70**	**50-50**	**40-60**	**30-70**
Outcome codes						
218	36,500	36,500	36,500	45,500	45,500	45,500
201	36,500	55,000	85,500	45,500	68,000	106,000
313	13,000	13,000	13,000	11,000	11,000	11,000
201	13,000	20,000	31,000	11,000	16,500	26,000

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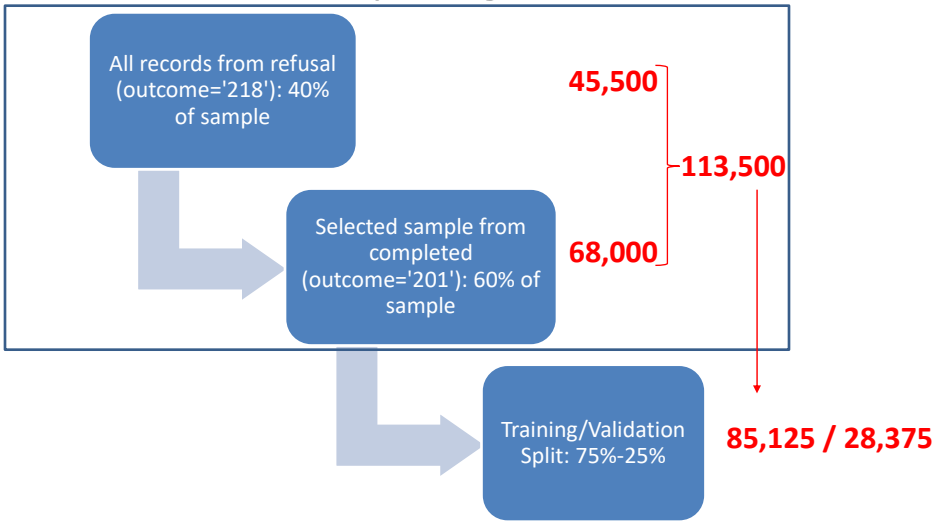
Prediction model setup (e.g. for 40/60 in 2018)



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Methods

- NLP (natural language processing)
  - TF-IDF vectorization (Term Freq, Inverse Document Freq)
- Machine Learning Models used
  - Logistic Regression (LR)
  - Random Forest (RF)
  - Gradient boosting – XG Boost (XGB)
  - Neural Network – Multi Layer Perceptron (MLP)
  - Support Vector Machine (SVM)

- **Accounts for procedural – or model – bias in results**

Model metrics

- **Accuracy:** number corrected predicted / total (n)
- **Precision:** true refusals / total refusals predicted
  - How many predicted refusals are actual refusals?
  - Good metric, if cost of wrong prediction of refusals is high
- **Recall:** true refusals predicted / total actual refusals
  - How many of the actual refusals have been predicted?
  - Good metric, if cost of gathering survey response is high
- **F1:** $F1 = 2 \times \frac{Precision * Recall}{Precision + Recall}$
  - Measures balance between precision and recall

Best model for respondent burden (201 vs. 313)

2017

	Random Forest											
	50-50				60-40				70-30			
Features used	**Accuracy (A)**	**Precision (P)**	**Recall (R)**	**F1-value**	A	P	R	F	A	P	R	F
CHI only	0.701	0.785	0.548	0.645	0.715	0.705	0.496	0.582	0.770	0.707	0.393	0.505
Notes only	0.739	0.811	0.618	0.702	0.812	0.804	0.701	0.749	0.852	0.880	0.584	0.702
CHI + Notes (All Features)	0.790	0.765	0.856	0.808	0.832	0.808	0.761	0.784	0.864	0.833	0.683	0.751
CHI + Notes (best 2k)	0.798	0.772	0.862	0.814	0.829	0.799	0.767	0.783	0.864	0.827	0.689	0.752

2018

	50-50				60-40				70-30			
Features used	**Accuracy (A)**	**Precision (P)**	**Recall (R)**	**F1-value**	A	P	R	F	A	P	R	F
CHI only	0.721	0.682	0.860	0.761	0.715	0.705	0.496	0.582	0.770	0.707	0.393	0.505
Notes only	0.757	0.742	0.809	0.774	0.812	0.804	0.701	0.749	0.852	0.880	0.584	0.702
CHI + Notes (All Features)	0.790	0.765	0.856	0.808	0.832	0.808	0.761	0.784	0.864	0.833	0.683	0.751
CHI + Notes (best 2k)	0.798	0.772	0.862	0.814	0.829	0.799	0.767	0.783	0.864	0.827	0.689	0.752

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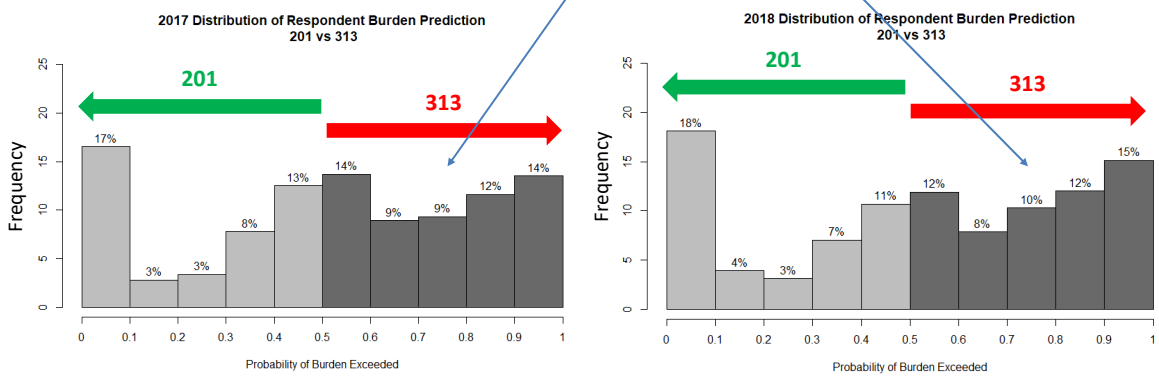
Distribution of Probability of Final outcome based on first contact only (201 vs. 313)

Differentiated strategies can be implemented for these segments



Model with CHI + Notes (All features), 50-50 undersampling ratio

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Best model for respondent refusal (201 vs. 218)

- Similar as in 201 vs. 313 modeling
- Best model:
  - CHI + Notes (all features), Random Forest, 40-60 undersampling
- Notes-only model accuracy 20-25% better than CHI-only model
- Probability distribution of final outcome can provide differentiated strategies for operational implementation

Feature importance

- Mix of CHI and Case Notes terms (single and double-word phrases)
- Can be used to spot refusal reason trends in different times and geographies
- Can be used to train FR

Transfer learning
Response propensity – 201 vs. 218

- Train on 2017 data, predict 2018
- Choose best trained model from 2017
  - Random Forest, 50-50 undersampling
- Predict refusals (218) for 2018
  - 2018 Jan-Mar
  - 2018 Jan-June
  - 2018 full year
- Insights:
  - Model accuracies dropped, as expected
  - Need to build rolling horizon model
  - Add state and RO (geographic dimension)
  - Add month of survey (time dimension)

Deep learning modeling ongoing

- Predictors:
  - CHI
  - Case Notes
  - State and RO (regional office) } geographic dimension
  - Survey month } time dimension
- Methods:
  - NLP: NER (Named Entity Recognition), ELMo, BERT

Conclusion and next steps

- Promising results from CHI + Case Notes predictive model
  - Used only 1st contact information to predict eventual outcome
  - Augmenting with newer datasets (2019, 2020)
- Can provide reliable recommendations for eventual refusal cases
- Provide highly confident refusal recommendations
  - Lower the data collection priority on predicted cases (eventual refusals)
  - Add a high value to burden score
- Can lead to savings in data collection
  - Cost of each contact/case
- Continue to fine-tune models
  - Deep learning models

- Experiment: For medium confident refusal recommendations, use some treatment to see if it increases response rate