Modelling Final Outcome and Length of Call Sequence to Improve Efficiency in Call Scheduling

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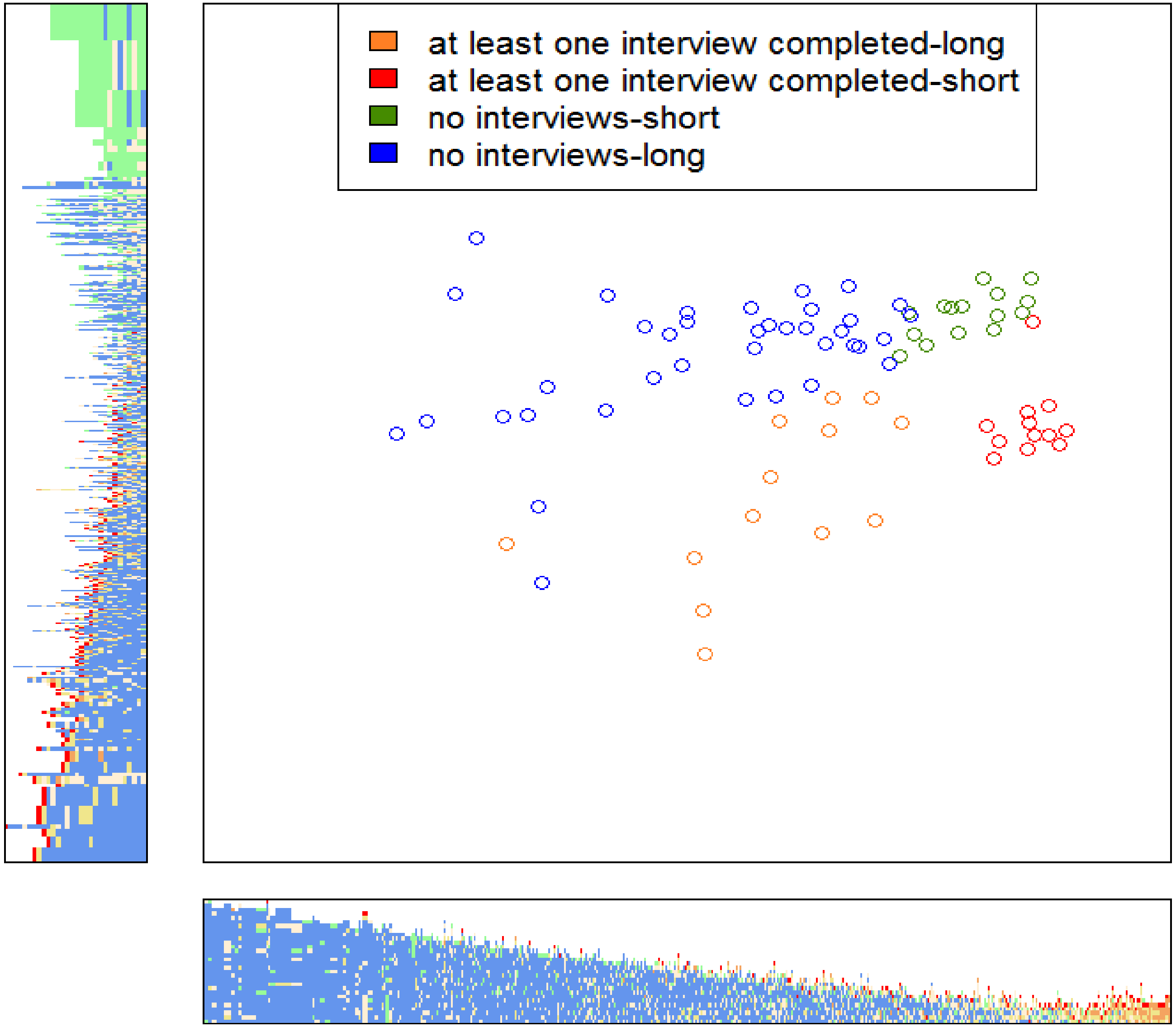
Motivation

Survey practice:

- Aim for short call sequences and success in gaining response
- Aim to avoid unsuccessful and/or long call sequences since these are resource intensive

Motivation: Sequence Analysis



For interviewer 11002071

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Main Research Question

- Can we predict final call sequence length and final outcome early on in the data collection process?
- In other words:
  - Can we predict say after the third call if a household is going to respond or not ?
  - How many calls is it going to take to get the outcome?

➢ This would help survey agencies to make a more informed decision of who to continue to follow up

➢ Particularly useful for longitudinal surveys

Further Research Questions

- Ability of 'classical' nonresponse models without call data to predict nonresponse is often limited (R^2 values well below 10%)
- How predictive are the models proposed here including call record data?
- Does their ability to predict improve once more call record data are available (e.g. for later calls; or for later waves in a longitudinal study)?
- How can predictors best be incorporated into the models (summary measures or individual outcomes)?
- How can these models best be used in adaptive and responsive survey designs?

A Note:

- Previously developed: discrete time event history analysis to model response outcome at next call
- Analysis here provides a simple example of how to use call record data
- Applicable to call record data from CAPI or CATI
- For analysis of both cross-sectional and longitudinal surveys

Data

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Data

- UK Understanding Society Survey
- Large-scale longitudinal study
- Call data from Wave 1 only (Jan 2009- March 2011)
- Face-to-face interviews of all adult household members
- Minimum of 6 calls made to a household per survey guidance
- Analysis sample: 25,358 households within 734 interviewers

Note: for the purpose of this analysis need to compare models on the same data (same cases). Therefore, analysis restricted to cases with at least 4 calls (not necessary in survey practice)

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Analysis Methods

Dependent Variables and Models

Dependent Variable	Categorisation	Model
a. Length	Short (1-6 calls) vs long (7+)	Binary logistic
b. Outcome	Successful (at least one interview) vs unsuccessful	Binary logistic
c. Length x outcome	4 categories: Short successful Short unsuccessful Long successful Long unsuccessful	Multinomial logistic

Households clustered within interviewers ⇒used robust SE estimation

Modelling strategy and explanatory variables

Model	Explanatory Variables
0.) Before data collection (Before call 1)	Geographical information only
	Plus interviewer observation variables
1.) After call 1	Plus call data from first call (outcome; day and time), time of next call)
2.) After call 3	Plus call data from second and third call (outcomes, day and time, time between calls), time of next call, time between call 3 and 4.

Assessment of Models

- Focus on ability of models to predict length and outcome
- To compare different models, to assess quality of model prediction and model fit
  - Pseudo-R^2 statistic (proportion of variation in the dependent variable that is explained by the model)
- Concept from epidemiology to assess accuracy of models (Plewis et al 2012):
  - discrimination (sensitivity and specificity)
  - prediction (positive and negative predicted value)

Assessment of Models

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- To assess both concepts: classification table is useful
- Say nonresponse $y = 1$, predicted value $\hat{\pi}$, then $\hat{y} = 1$ if $\hat{\pi} > c$
- Discrimination:
  - sensitivity: $P(\hat{y} = 1|y = 1)$
  - specificity: $P(\hat{y} = 0|y = 0)$
- Prediction:
  - Positive predicted value: $P(y = 1|\hat{y} = 1)$
  - Negative predicted value: $P(y = 0|\hat{y} = 0)$

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Results

Results

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Model	Length		Outcome		Length x Outcome	
	pseudo R^2	Classificat. Table	pseudo R^2	Classificat. Table	pseudo R^2	Classificat. Table
Before call 1: geography	3%	56%	1%	54%	3%	36%

Results

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Before call 1: geography	3%	56%	1%	54%	3%	36%
+ IO	6%	59%	6%	58%	9%	39%

Results

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+ IO	6%	59%	6%	58%	9%	39%
After call 1: + call 1 data	8%	60%	8%	60%	12%	40%

Results

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+ IO	6%	59%	6%	58%	9%	39%
After call 1: + call 1 data	8%	60%	8%	60%	12%	40%
After call 3: + call 1-3 data	11%	61%	11%	62%	19%	43%

Results

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After call 3: + call 1-3 data	11%	61%	11%	62%	19%	43%
+ call 3 outcome	25%	69%	27%	68%	36%	51%
+ calls 1-3 outcome	26%	70%	30%	70%	37%	52%

Results

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After call 3: + call 1-3 data	11%	61%	11%	62%	19%	43%
+ call 3 outcome	25%	69%	27%	68%	36%	51%
+ calls 1-3 outcome	26%	70%	30%	70%	37%	52%
+ 4 sums of outcome	22%	69%	30%	69%	33%	50%
+ call 4 data (without outcome)	27%	71%	32%	70%	40%	50%

Results: Sensitivity

Model	Short Unsuccessful (n=4962)	Short Successful (n=7391)	Long Unsuccessful (n=8603)	Long Successful (n=4402)
1	0.0%	43.2%	69.6%	0.0%
2	6.5%	52.8%	65.9%	0.1%
3	20.4%	49.8%	64.2%	0.1%
4	31.1%	51.6%	63.9%	0.4%
5	44.3%	50.2%	79.5%	5.2%
6	45.1%	51.0%	79.5%	5.6%
7	42.2%	54.4%	75.3%	3.9%
8	50.7%	52.5%	78.2%	6.8%

$$P(\hat{y} = k|y = k)\ (k = 1,2,3,4)$$

Of the long unsuccessful about 80% estimated correctly

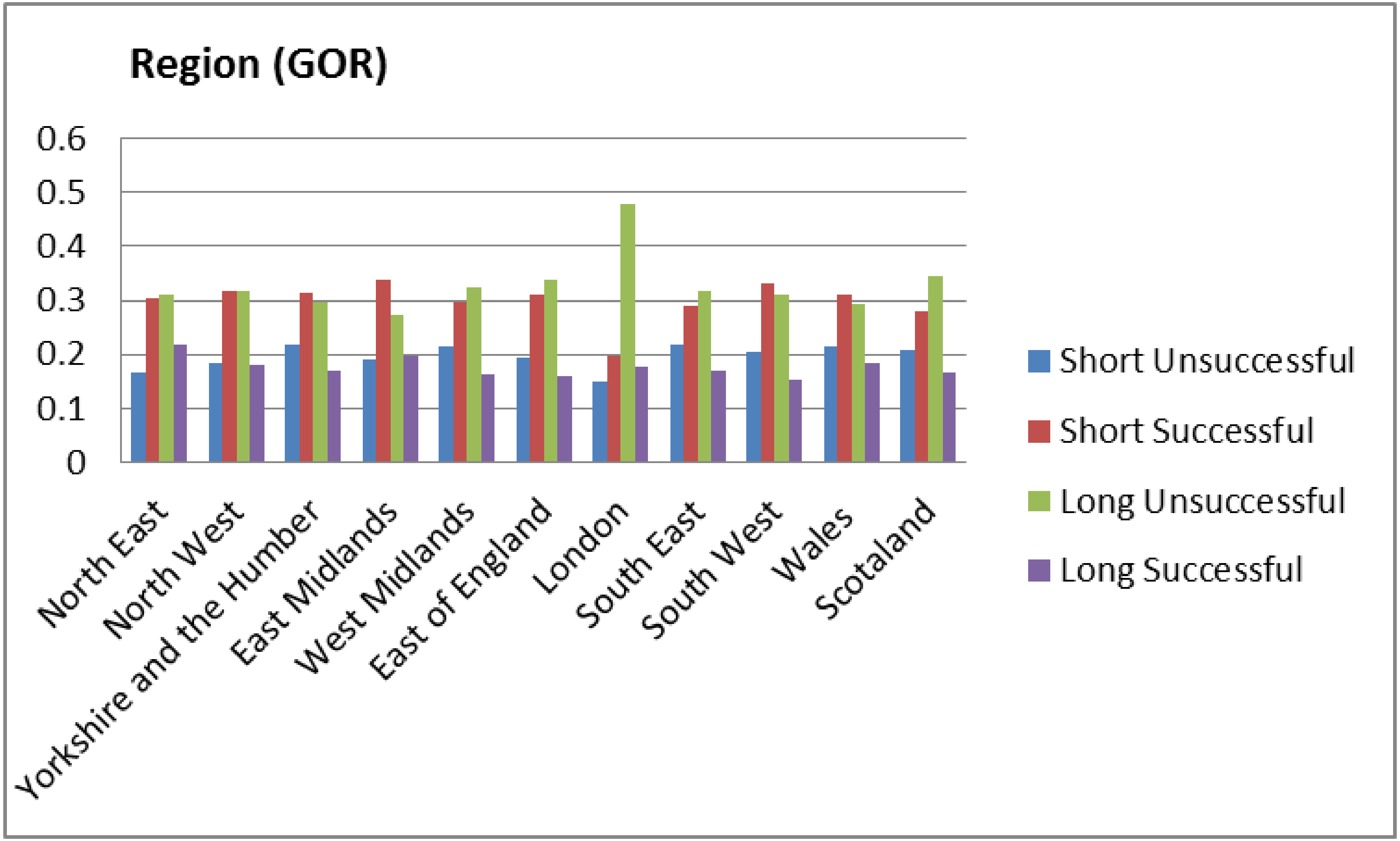
Results: Positive predicted value

		Short Unsuccessful (n=4962)	Short Successful (n=7391)	Long Unsuccessful (n=8603)	Long Successful (n=4402)
Predicted	Short Unsuccessful	58.7%	13.1%	22.1%	6.1%
	Short Successful	11.2%	63.6%	12.8%	12.4%
	Long Unsuccessful	13.4%	19.6%	45.7%	21.3%
	Long Successful	7.4%	28.3%	25.2%	39.1%

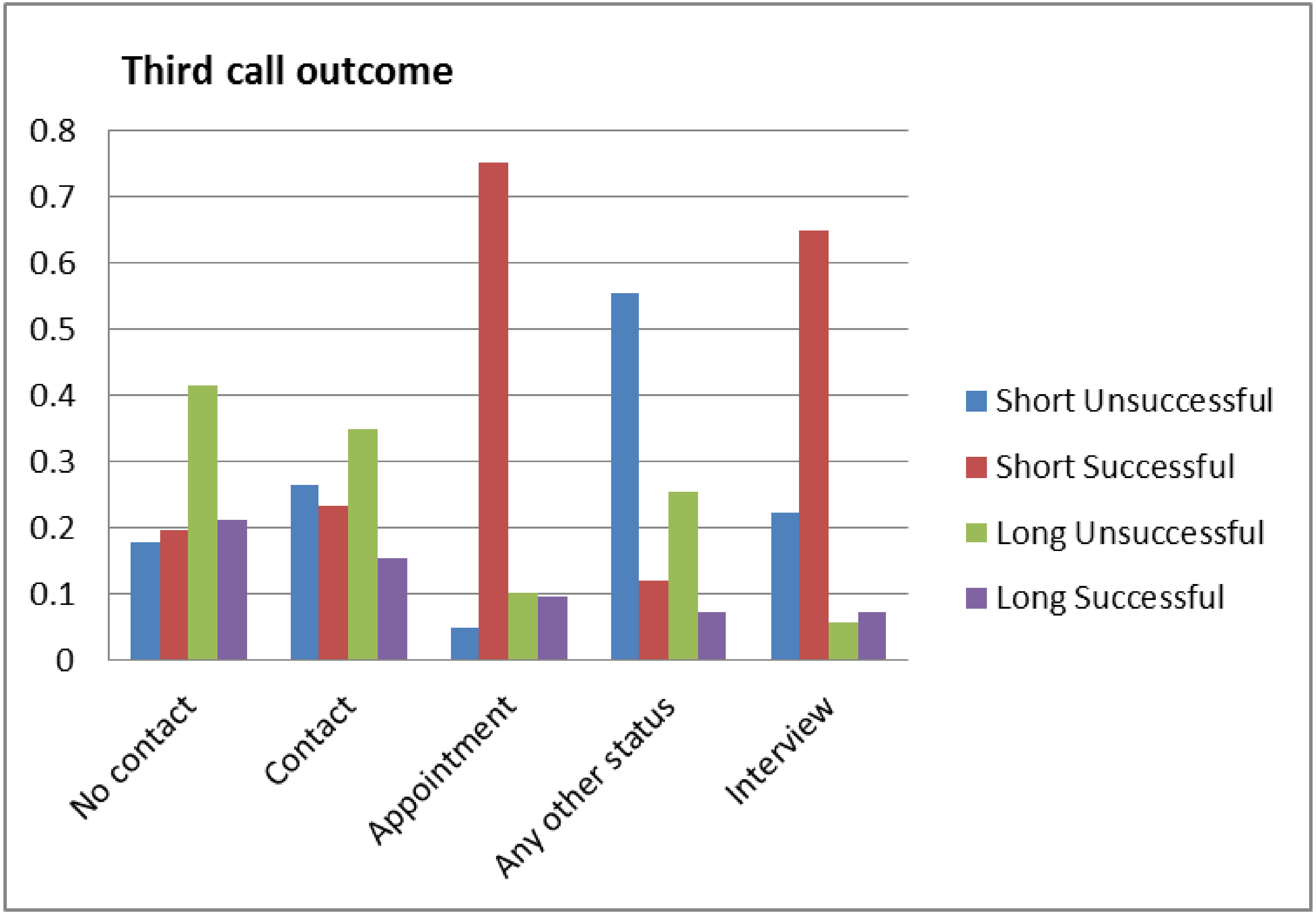
$P(y = k|\hat{y} = k)\ (k = 1,2,3,4)$

Of the cases predicted to be long unsuccessful 50% are indeed l.u.

Results: Predicted Values (multinomial)



Results: Predicted Values (multinomial)



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Summary of results (call data)

- Adding more and more call data increases prediction in comparison to no call data (pseudo-R^2 from 6% to around 30%)
- Adding outcome of previous call(s) significantly improves prediction (pseudo-R^2 from 11% to around 40%)
- Variables better entered as raw outcomes rather than as summary measures
- Time of calls and time between calls are all significant variables but their impact on prediction limited; day of the week not significant in models

Summary of results (2)

- Modelling length and final outcome jointly improves prediction
- Interviewer observation variables all significant; including them increases prediction, but in absolute terms improvement small
- Basic geographic information not very predictive; using call record data greatly improves predictive power

Conclusions

- Novel is to model sequence length and to model length and outcome jointly
- Potentially a simple idea using standard methodology
- Can be implemented into survey practice quite easily
- Survey managers may wish to weigh up between the probability of a successful outcome versus sequence length; other dependent variables possible too

Further work

- Use models for prediction at the next wave:
  - take estimated coefficients based on wave 1 data and use them to predict length and final call outcome for wave 2 data
  - assess how predicted length and outcome compare to the true outcomes from wave 2
- Use the same strategy on wave 2 call data for prediction at wave 3, using also prior information from wave 1 (survey data and call record data).
- Monitor nonresponse bias across calls (quality of the (non-) respondents) (work with Correa and Smith); prioritization of cases

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Thank you!

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(working paper available)

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A remark

- Cannot establish causal links but merely associations between the response and the explanatory variables since observational data and not experimental data
- However, not a limitation since aims to models for prediction and for comparison of different models (analysis does not need to establish causal links)