# Predicting Completion Conditions in Mobile Web Surveys with Acceleration Data

Christoph Kern[1] Stephan Schlosser[2] Jan Karem Hoehne[1, 3] Melanie Revilla[3]

[1]University of Mannheim

[2]University of Goettingen

[3]RECSM-Universitat Pompeu Fabra

ESRA Conference 17.07.2019

# Introduction

Motivation

- Smartphones allow respondents to take part in surveys irrespective of location and situation
- Measurement in mobile web surveys challenged by distractions (Lynn and Kaminska, 2012; Toninelli and Revilla, 2016)
  - Self-reports on distractions subject to error
  - Paradata on browser tab switching limited to on-device multitasking

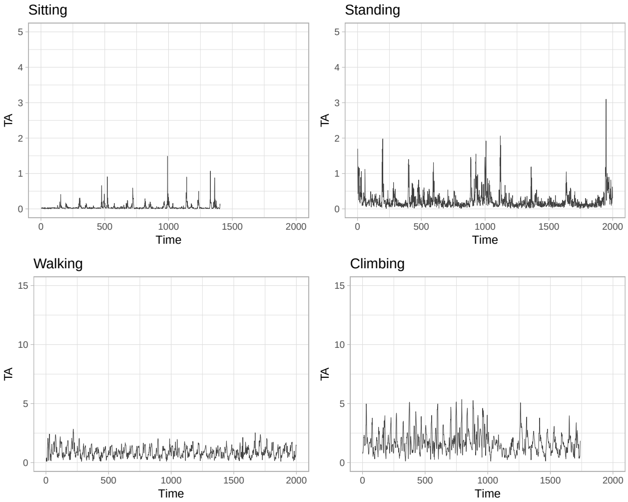
→ Utilizing acceleration data from smartphone sensors and machine learning to infer **completion conditions**

1. Can we accurately predict respondents completion conditions by using acceleration data?
2. Do respondents with different completion conditions differ in terms of response behavior?

# SurveyMotion

- JavaScript-based paradata tool (Höhne and Schlosser, 2019)
- Measures the total acceleration (TA)
- Code can be implemented as an invisible, user-defined question in a web survey page

Figure: Examples of total acceleration profiles



# Data

**Training data**: Lab experiment

- Data collected in August 2017 at the University of Goettingen (Höhne and Schlosser, 2019)
- 89 university students
- Completed mobile web survey in one of four experimental groups
  - First group was seated in front of a desk
  - Second group stood at a fixed point
  - Third group walked along an aisle
  - Fourth group climbed stairs

**Prediction**: Cross-sectional web survey

- Data collected in December 2017 at the University of Goettingen (Schlosser and Höhne, 2018)
- 2,357 respondents
- 61.6% smartphone respondents
  - Acceleration data available for 97,2% of smartphone respondents

# Analytical Strategy

Variables (respondent-pages)

- Outcome
  - 4 class outcome: sitting, standing, walking, climbing stairs
  - 2 class outcome: **moving** (walking, climbing stairs), **not moving** (sitting, standing)
- Predictors
  - Aggregated TA measurements

Training and evaluation

- ML methods
  - Elastic net (GLMnet; Friedman et al. 2010)
  - Conditional Inference Trees (CTREE; Hothorn and Zeileis 2015)
  - Random Forests and Extremely Randomized Trees (RF; Wright and Ziegler 2017)
  - Extreme Gradient Boosting (XGBoost; Chen and Guestrin 2016)
- 10-Fold Cross-Validation (grouped by respondent IDs)

# Model Evaluation

Figure: Cross-Validation results (training set)

(a) 4 class outcome　　(b) 2 class outcome

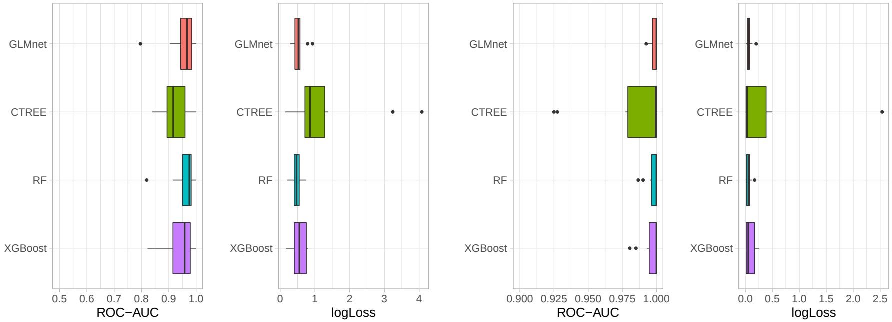



Table: Confusion tables (training set)

(a) 4 class outcome

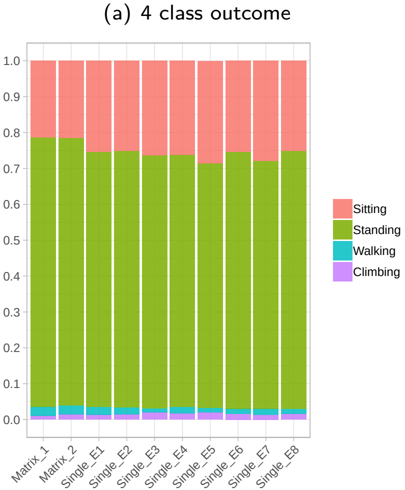
| | Sitting | Standing | Walking | Climbing |
|---|---|---|---|---|
| Sitting | 21.105 | 1.983 | 0.000 | 0.000 |
| Standing | 3.399 | 21.671 | 0.567 | 0.000 |
| Walking | 0.000 | 0.850 | 17.564 | 4.958 |
| Climbing | 0.000 | 0.283 | 7.932 | 19.688 |

(b) 2 class outcome

| | Not_Moving | Moving |
|---|---|---|
| Not_Moving | 48.017 | 0.567 |
| Moving | 1.275 | 50.142 |

# Prediction

Figure: Class predictions in web survey



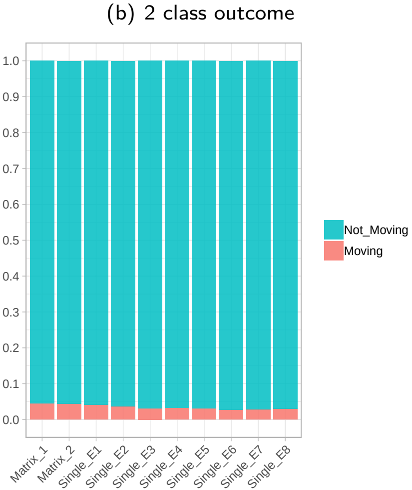



Figure: Sequences of predicted motion conditions in web survey

# Group Comparisons

Table: Mixed effects regressions modeling completion time[1]

| | *Dependent variable* | | | |
|---|---|---|---|---|
| | Completion time | | | |
| | (1) | (2) | (3) | (4) |
| Moving | 0.906 | 0.801 | 0.799 | 0.649 |
| *se* | (0.330) | (0.334) | (0.334) | (0.372) |
| *p* | 0.007 | 0.017 | 0.017 | 0.081 |
| Matrix | | | 28.742 | 28.720 |
| *se* | | | (0.983) | (0.983) |
| *p* | | | 0.000 | 0.000 |
| Moving × Matrix | | | | 0.567 |
| *se* | | | | (0.623) |
| *p* | | | | 0.363 |
| Constant | 13.033 | 13.134 | 7.386 | 7.391 |
| *se* | (3.857) | (3.853) | (0.466) | (0.466) |
| Demographic controls | | *X* | *X* | *X* |
| Observations | 11,029 | 10,688 | 10,688 | 10,688 |
| Bayesian Inf. Crit. | 68,040.810 | 65,779.330 | 65,744.750 | 65,752.300 |

[1] Completion time outliers excluded based on .05 and .95 quantile.

# Group Comparisons

Table: Generalized mixed effects regressions modeling intra-individual response variability and primacy effects

| | *Dependent variable* | | | | |
|---|---|---|---|---|---|
| | irv20 | irv80 | | primacy | |
| | (1) | (1) | (1) | (2) | (3) |
| Moving | −0.251 | −0.614 | −0.016 | −0.016 | 0.290 |
| *se* | (0.280) | (0.400) | (0.103) | (0.103) | (0.161) |
| *p* | 0.369 | 0.125 | 0.880 | 0.879 | 0.072 |
| Matrix | | | | 0.573 | 0.589 |
| *se* | | | | (0.778) | (0.766) |
| *p* | | | | 0.462 | 0.442 |
| Moving × Matrix | | | | | −0.430 |
| *se* | | | | | (0.178) |
| *p* | | | | | 0.016 |
| Constant | −1.444 | −1.458 | −1.435 | −1.551 | −1.562 |
| *se* | (0.112) | (0.149) | (0.320) | (0.350) | (0.347) |
| Demographic controls | *X* | *X* | *X* | *X* | *X* |
| Observations | 2,362 | 2,362 | 28,338 | 28,338 | 28,338 |
| Bayesian Inf. Crit. | 2,664.197 | 2,344.515 | 30,685.030 | 30,694.740 | 30,699.390 |

# Discussion

Summary

- High cross-validated prediction accuracy for 4 class and 2 class outcome in training data
- Low rate of respondents with predicted high motion levels (e.g., walking) in web survey
- Modest differences in terms of data quality proxies between motion groups

Next steps

- Add further quality indicators for group comparisons
- Compare predicted classes with simple mean split (high vs. low average TA)
- Predict and compare groups in additional web survey

# Contact

Contact: c.kern@uni-mannheim.de

# References


Chen, T. and Guestrin, C. (2016). XGBoost: A scalable tree boosting system. `https://arxiv.org/abs/1603.02754`.

Friedman, J., Hastie, T., and Tibshirani, R. (2010). Regularization paths for generalized linear models via coordinate descent. *Journal of Statistical Software*, 33(1):1–22.

Höhne, J. K. and Schlosser, S. (2019). SurveyMotion: What can we learn from sensor data about respondents' completion and response behavior in mobile web surveys? International Journal of Social Research Methodology.

Hothorn, T. and Zeileis, A. (2015). partykit: A modular toolkit for recursive partytioning in R. *Journal of Machine Learning Research*, 16:3905–3909.

Lynn, P. and Kaminska, O. (2012). The impact of mobile phones on survey measurement error. *Public Opinion Quarterly*, 77:586–605.

Schlosser, S. and Höhne, J. K. (2018). Sensor data: Measuring acceleration of smartphones in mobile web surveys. Poster presented at the general online research conference, Cologne, Germany.

Toninelli, D. and Revilla, M. (2016). Smartphones vs pcs: Does the device affect the web survey experience and the measurement error for sensitive topics? a replication of the mavletova & couper's 2013 experiment. *Survey Research Methods*, 10:153–169.

Wright, M. N. and Ziegler, A. (2017). ranger: A fast implementation of random forests for high dimensional data in C++ and R. *Journal of Statistical Software*, 77(1):1–17.