Digital Footprints of Sensation Seeking: A Traditional concept in the Big Data Era

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Automated Trait Recognition

Prediction of traits from everyday digital technology usage

- Social network data (e.g. Kosinski, Stillwell, & Graepel, 2013)
- Smartphone data (Chittaranjan, Blom, & Gatica-Perez, 2013; Montjoye et al., 2013)

Sensation Seeking

- seeking varied, novel, complex, and intense sensations and experiences
- willingness to take physical, social, legal, and financial risks (Zuckerman, 1994)

- Focus of previous research:
  - unsocialized expression of sensation seeking (Roberti, 2004)
  - high risk activities (Zabel, Christopher, Marek, Wieth, & Carlson, 2009; Jack & Ronan, 1998)
  - self-reported behavior (Dahlen, Martin, Ragan, & Kuhlmann, 2005; Leung, 2008)

? Socialized expression

? Everyday manifestation

? Objective behavioral data

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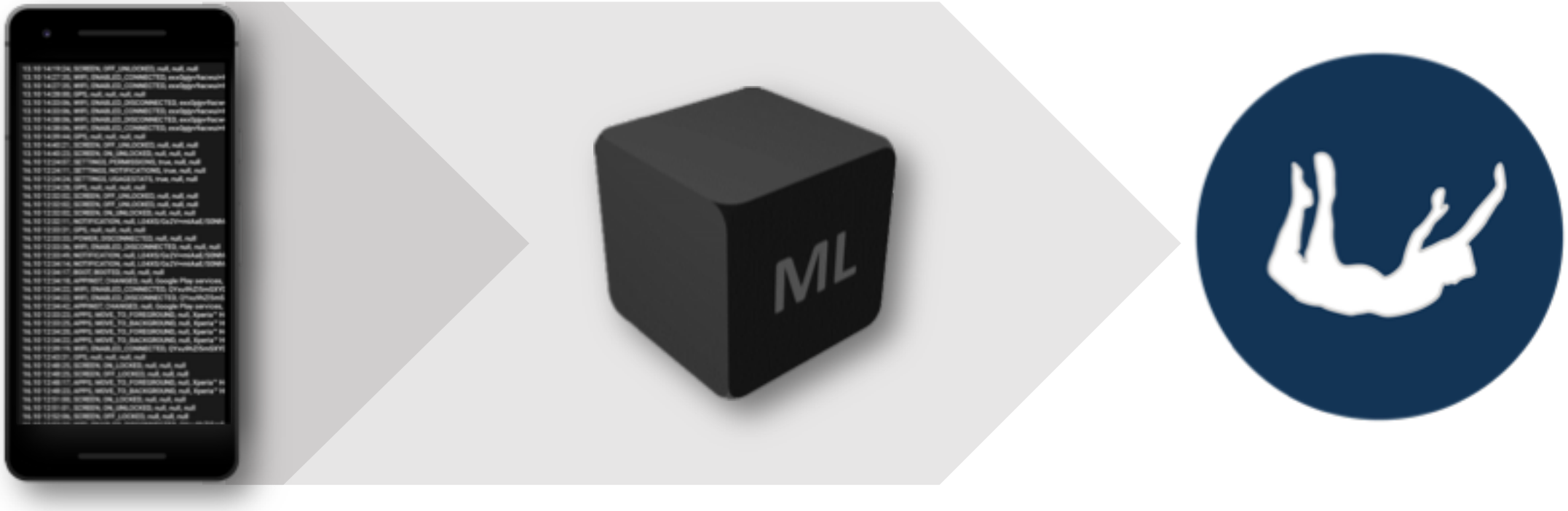
Smartphone Sensing

- ✓ Socialized expression
  - data about mobility, everyday activities and habits
- ✓ Everyday manifestation
  - digital behavior partly replaces "analog" behavior (Mayer-Schönberger & Cukier, 2013)
- ✓ Objective behavioral data
  - collection of extensive records of individual behavior (Harari et al., 2016)
    - efficient
    - unobtrusive

Can individual Sensation Seeking scores be reliably predicted from data collected via Smartphone Sensing?



PhoneStudy Research App

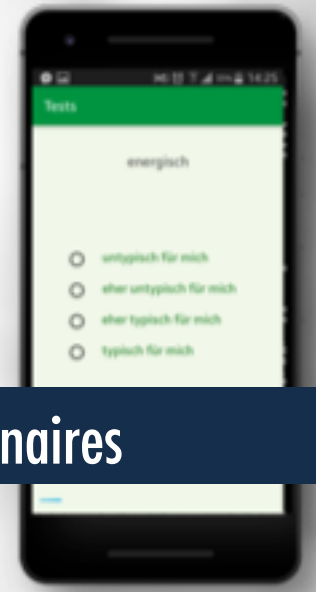
Data logging (GPS, app usage, phone calls)

Data collection

October 2017 – January 2018
30 days of data logging per individual

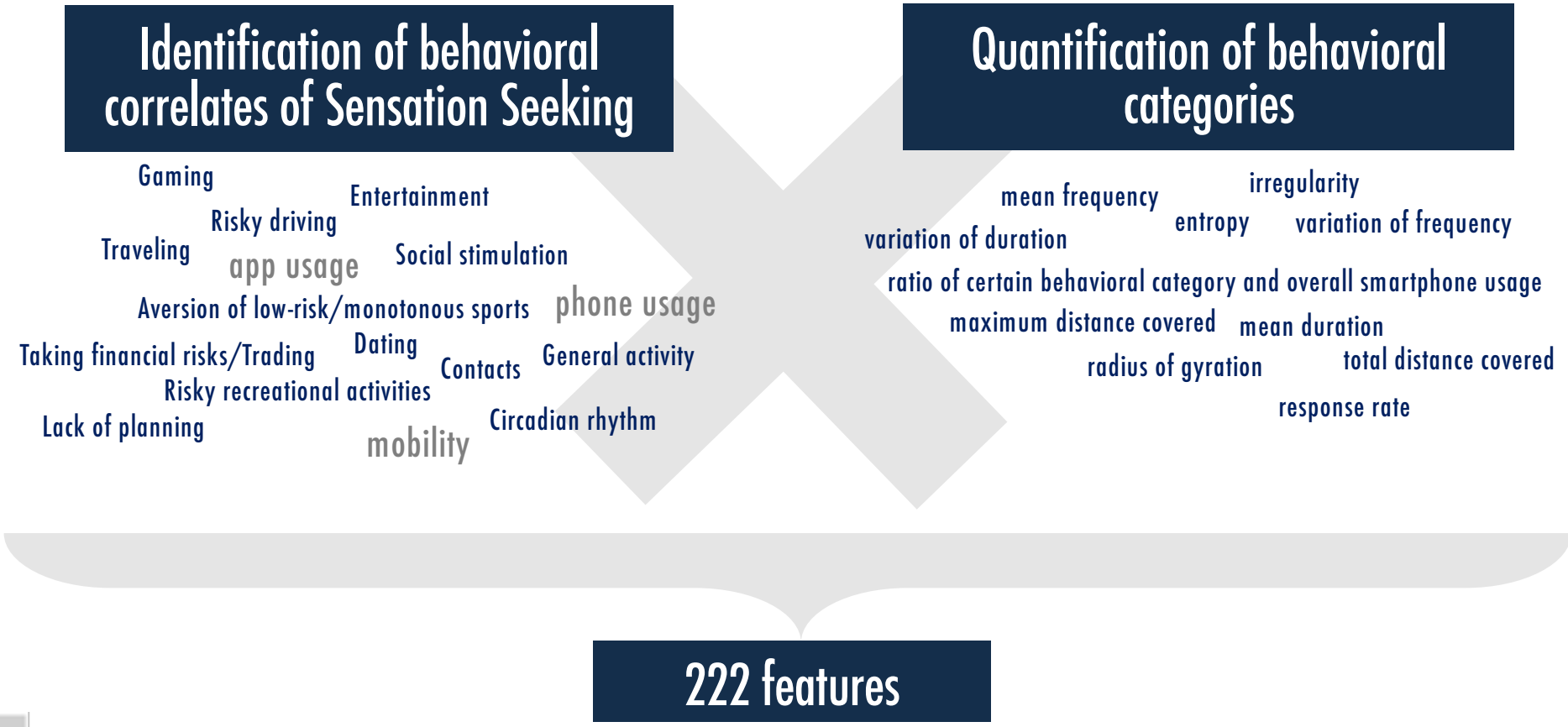
Sample

N = 260
68% women
average age of 24 (*SD* = 8.82, *RANGE* = 18 – 72)



Self-report Questionnaires

Features


Identification of behavioral correlates of Sensation Seeking
Gaming
Entertainment
Risky driving
Traveling
app usage
Social stimulation
Aversion of low-risk/monotonous sports
phone usage
Taking financial risks/Trading
Dating
Contacts
General activity
Risky recreational activities
Lack of planning
mobility
Circadian rhythm
Quantification of behavioral categories
irregularity
mean frequency
entropy
variation of frequency
variation of duration
ratio of certain behavioral category and overall smartphone usage
maximum distance covered
mean duration
radius of gyration
total distance covered
response rate
222 features

Criterion

- Assessed by the Impulsive Sensation Seeking Scale (ZKPQ-III-R; Zuckerman, 2002)
- True or False?
  - "I am an impulsive person"
  - "I usually think about what I am going to do before I do it"
- 19 items
- Cronbach's α = 0.83

Benchmark Experiment

- Comparison of:
  - featureless learner
  - random forest
  - extreme gradient boosting
  - support vector machine with RBF Kernel
  - elastic net
- Resampling:
  - Outer: 10 x 10-fold CV
  - Inner: Holdout
- Statistical Software R (mlr package, Bischl et al., 2016)

Descriptive Statistics

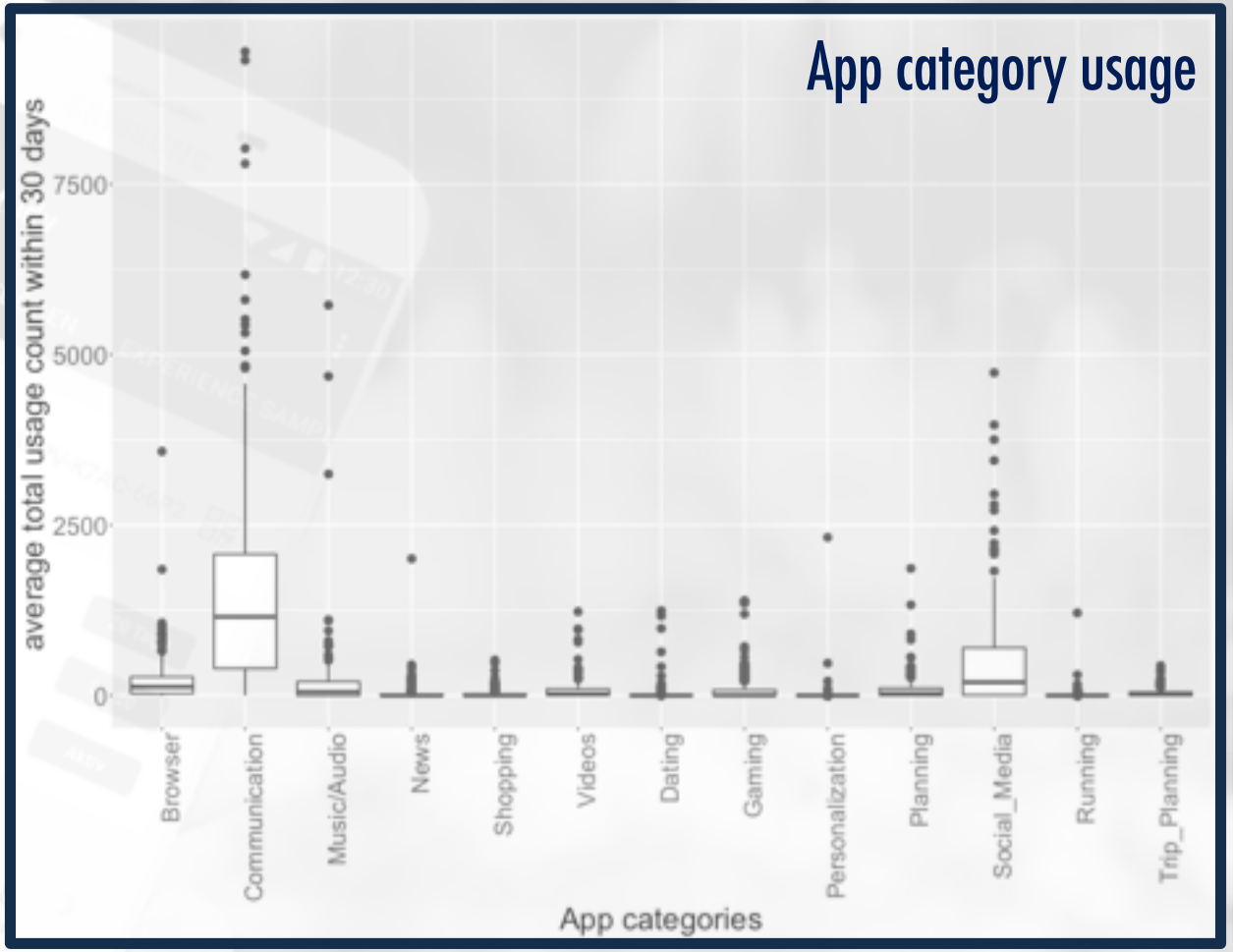
Sensation Seeking
RANGE = 0 - 19
M = 7.91, *SD* = 4.22

1263 daily events per person per day

2205 different apps

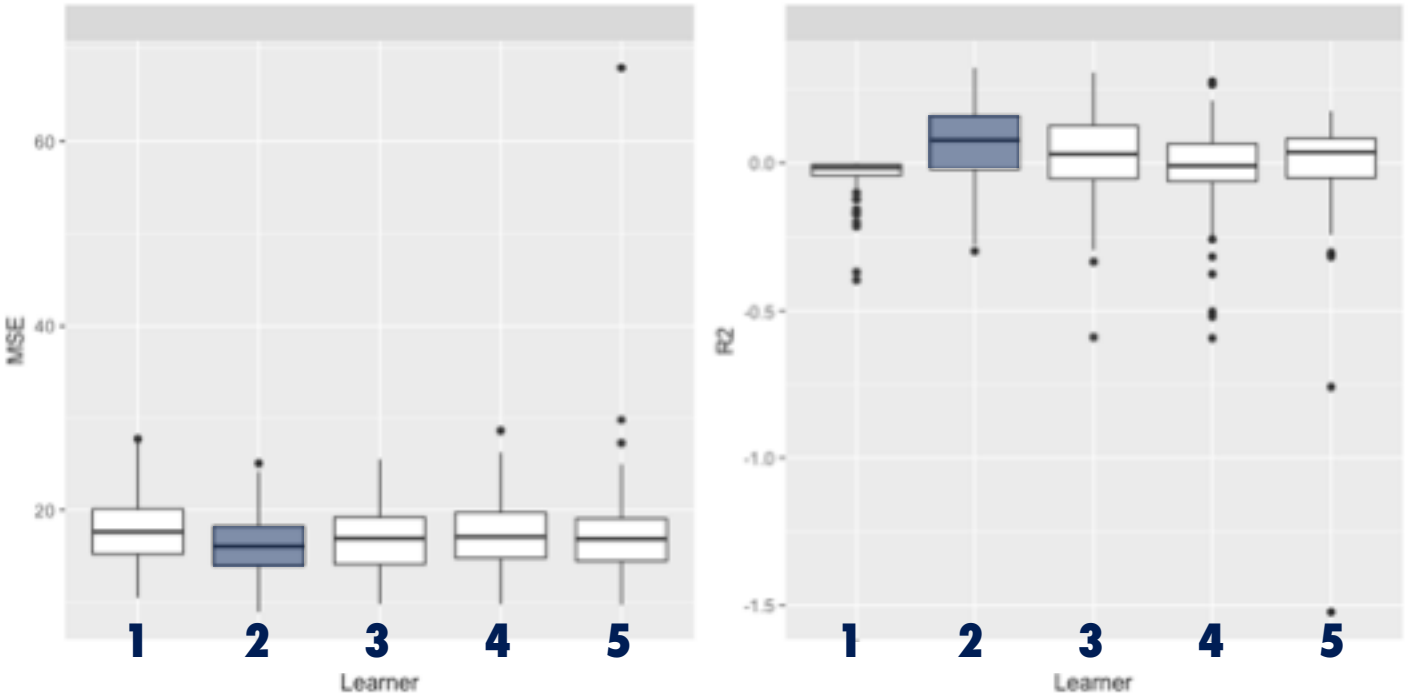
Top 10 used apps:

- Whatsapp
- Facebook
- Google Chrome
- Instagram
- Snapchat
- Spotify
- Jodel
- YouTube
- Samsung Internet Browser
- Google Maps

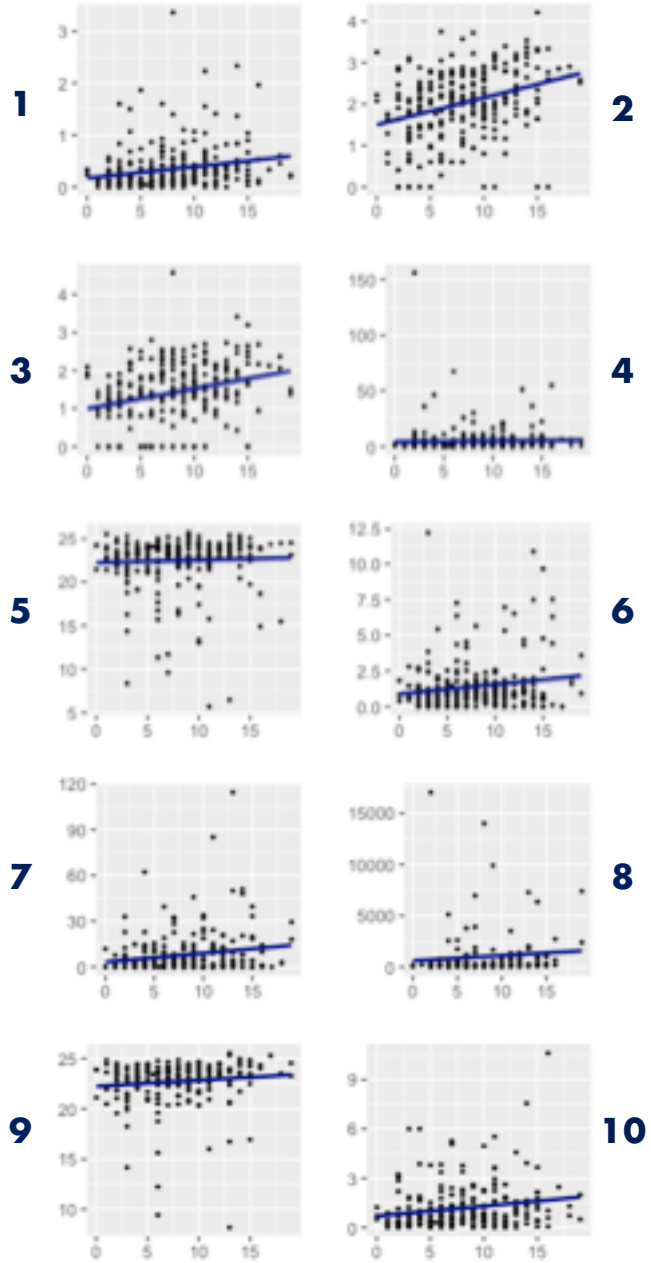


Benchmark experiment

		MSE	R^2
1	featureless learning	17.83	- 0.04
2	random forest	16.03	0.06
3	extreme gradient boosting	16.71	0.02
4	support vector machine	17.35	- 0.02
5	elastic net	17.43	- 0.01



Top 10 Features	Permutation-based Importance	
Mean frequency of missed calls per day	0.62	1
Entropy of contacts for outgoing calls	0.51	2
Entropy of contacts for missed calls	0.41	3
Variation of frequency of outgoing calls per day	0.32	4
Mean time of the last event on Friday/Saturday	0.21	5
Variation of the time of the first event from Monday to Friday	0.17	6
Mean number of intended events during night on Friday/Saturday	0.14	7
Mean radius of gyration during night on Friday/Saturday	0.14	8
Mean time of the last event on Sunday	0.14	9
Mean frequency of outgoing calls per day	0.13	10

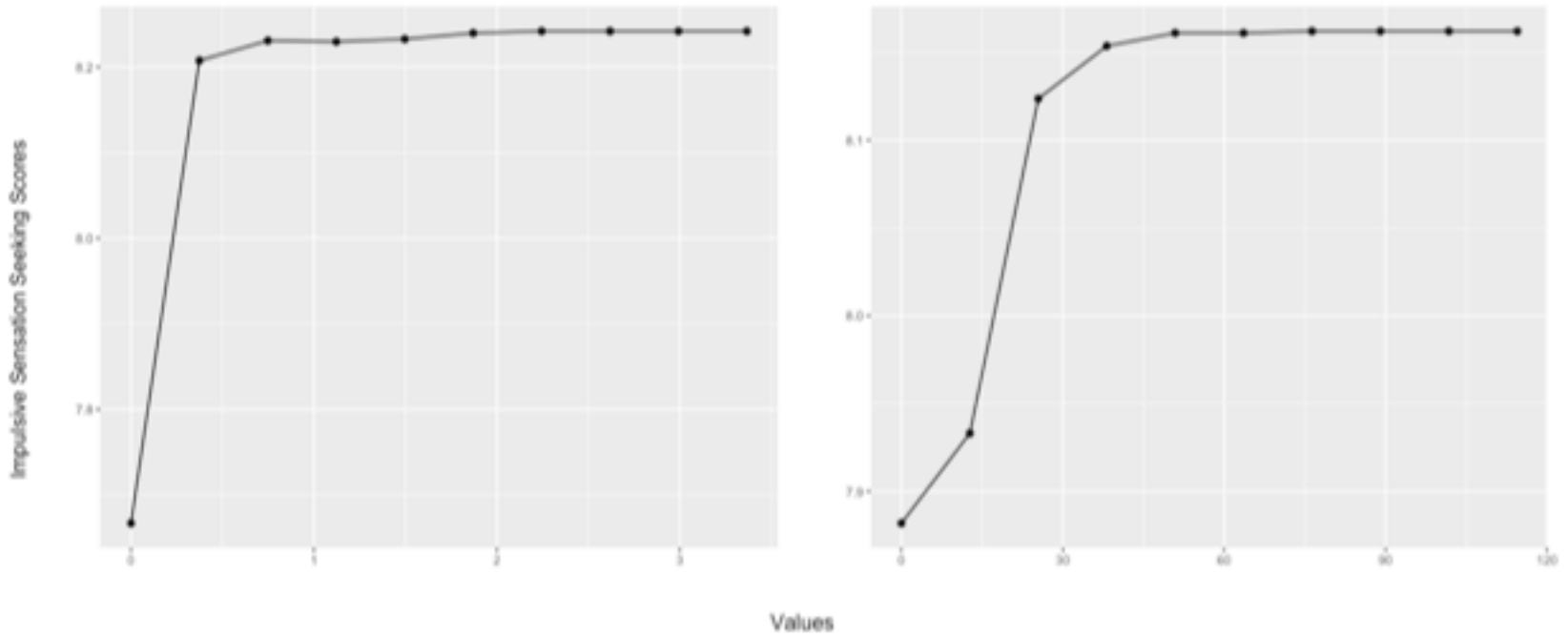


Sensation Seeking Scores

Partial dependence plots

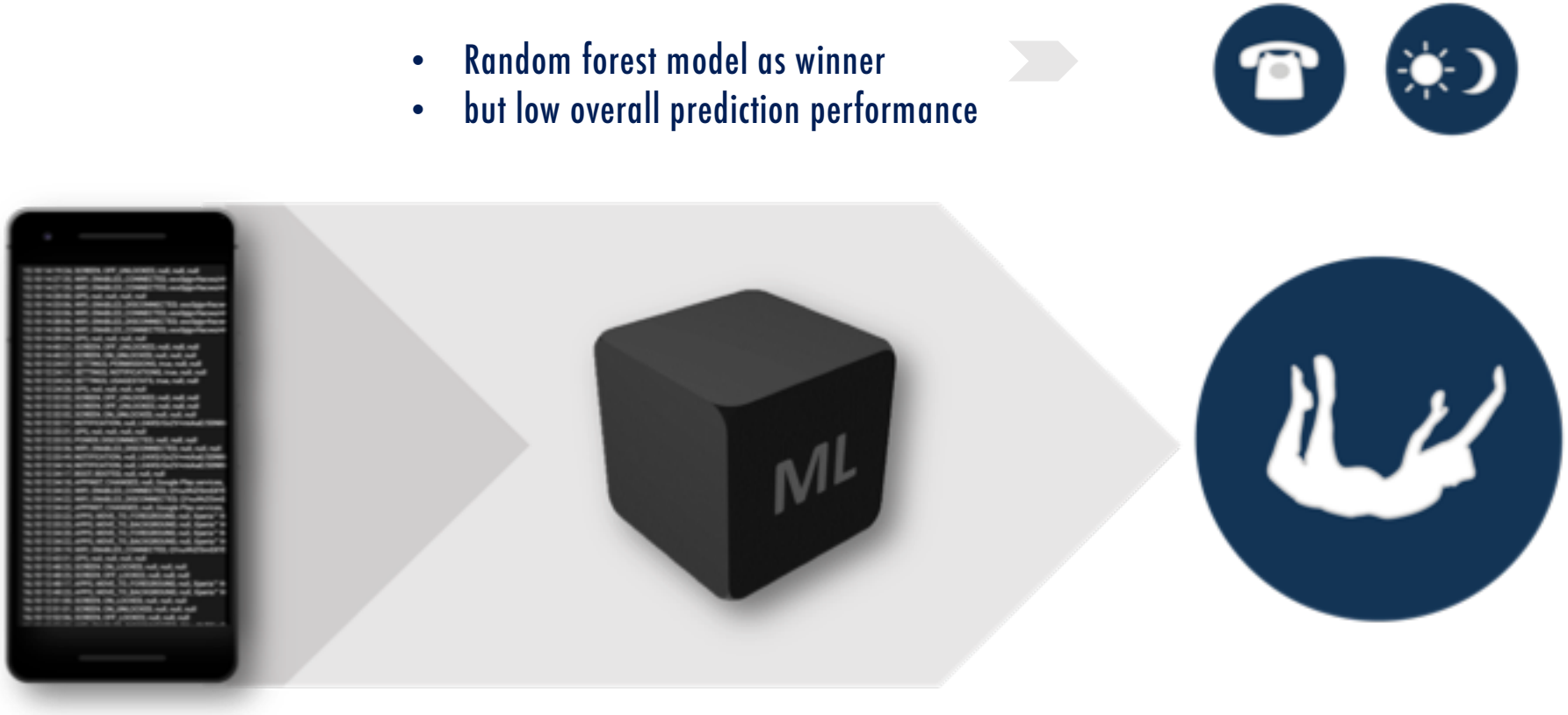
Mean frequency of missed calls per day

Mean number of intended events on Friday/Saturday night



Conclusion & Contribution

- Random forest model as winner
- but low overall prediction performance



Limitations & Outlook

- Ambiguous meta-data versus individual privacy rights?
- Sample: composition and size
- Self-reported trait scores as ground truth?

Thank you!

Questions or comments?

Please contact me at

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References

Bischl, B., Lang, M., Kotthoff, L., Schiffner, J., Richter, J., Studerus, E., . . . Jones, Z. M. (2016). mlr: Machine learning in r. *Journal of Machine Learning Research, 17 (170)*, 1–5. Retrieved from http://jmlr.org/papers/v17/15-066.html

Dahlen, E. R., Martin, R. C., Ragan, K., & Kuhlman, M. M. (2005). Driving anger, sensation seeking, impulsiveness, and boredom proneness in the prediction of unsafe driving. *Accident Analysis & Prevention, 37 (2), 341–348*. doi:10.1016/j.aap.2004.10.006

Harari, G. M., Lane, N. D., Wang, R., Crosier, B. S., Campbell, A. T., & Gosling, S. D. (2016). Using smartphones to collect behavioral data in psychological science: Opportunities, practical considerations, and challenges. *Perspectives on Psychological Science, 11(6),* 838–854. doi:10.1177/1745691616650285

Kosinski, M., Stillwell, D., & Graepel, T. (2013). Private traits and attributes are predictable from digital records of human behavior. *Proceedings of the National Academy of Sciences, 110(15),* 5802–5805. doi:10.1073/pnas.1218772110

Mayer-Schönberger, V., & Cukier, K. (2013). Big data: A revolution that will transform how we live, work, and think. Houghton Mifflin Harcourt.

Montjoye, Y.-A. de, Quoidbach, J., Robic, F., & Pentland, A. S. (2013). Predicting personality using novel mobile phone-based metrics. In *International conference on social computing, behavioral-cultural modeling, and prediction (pp. 48–55)*. Springer. doi:10.1007/978-3-642-37210-0_6

Chittaranjan, G., Blom, J., & Gatica-Perez, D. (2013). Mining large-scale smartphone data for personality studies. *Personal and Ubiquitous Computing, 17(3),* 433–450. doi:10.1007/s00779-011-0490-1

Roberti, J. W. (2004). A review of behavioral and biological correlates of sensation seeking. *Journal of Research in Personality, 38 (3),* 256–279. doi:10.1016/S0092-6566(03)00067-9

Zabel, K. L., Christopher, A. N., Marek, P., Wieth, M. B., & Carlson, J. J. (2009). Mediational effects of sensation seeking on the age and financial risk-taking relationship. *Personality and Individual Differences, 47 (8),* 917–921. doi:10.1016/j.paid.2009.07.016

Zuckerman, M. (1994). Behavioral expressions and biosocial bases of sensation seeking. Cambridge university press.

Zuckerman, M. (2002). Zuckerman-kuhlman personality questionnaire (zkpq): An alternative five-factorial model. *Big Five Assessment,* 377–396.

Appendix

Resampling

App categories & Sensation Seeking