Cognitive Load Inference for Ubiquitous Computing Adaptation

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University of Novi Sad, June 2019

Background

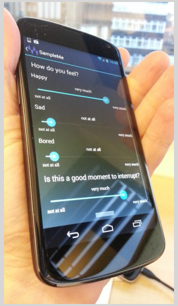
- PhD University of California Santa Barbara, CA, USA
  - Resource-efficient wireless solutions for rural areas
- Postdoc Uni. of Birmingham, UK
  - Mobile sensing for behaviour change interventions
- Assistant Professor at University of Ljubljana
  - Leading mobile computing research

Research Areas

More at: lrss.fri.uni-lj.si/Veljko

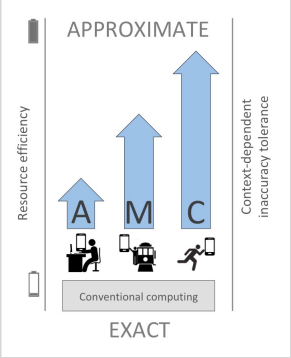
- Mobile sensing and user behaviour modelling

We built mobile apps, conduct user studies, and engineer innovative approaches for notification management



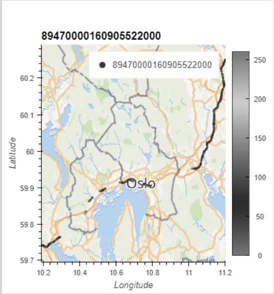
- Resource-efficient computing

We propose approximate mobile computing where the accuracy of computation changes with the context of use



- Mobile network data analysis

We build data mining tools for network traffic analysis



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University of Ljubljana

- The oldest, largest, best-ranked university in Slovenia
- Top 500 on Shanghai, Webometrics, Times ranking lists
- Faculty of computer and information science (FRI)
  - 170 employees
  - 1400 students
  - BS/MS/PhD

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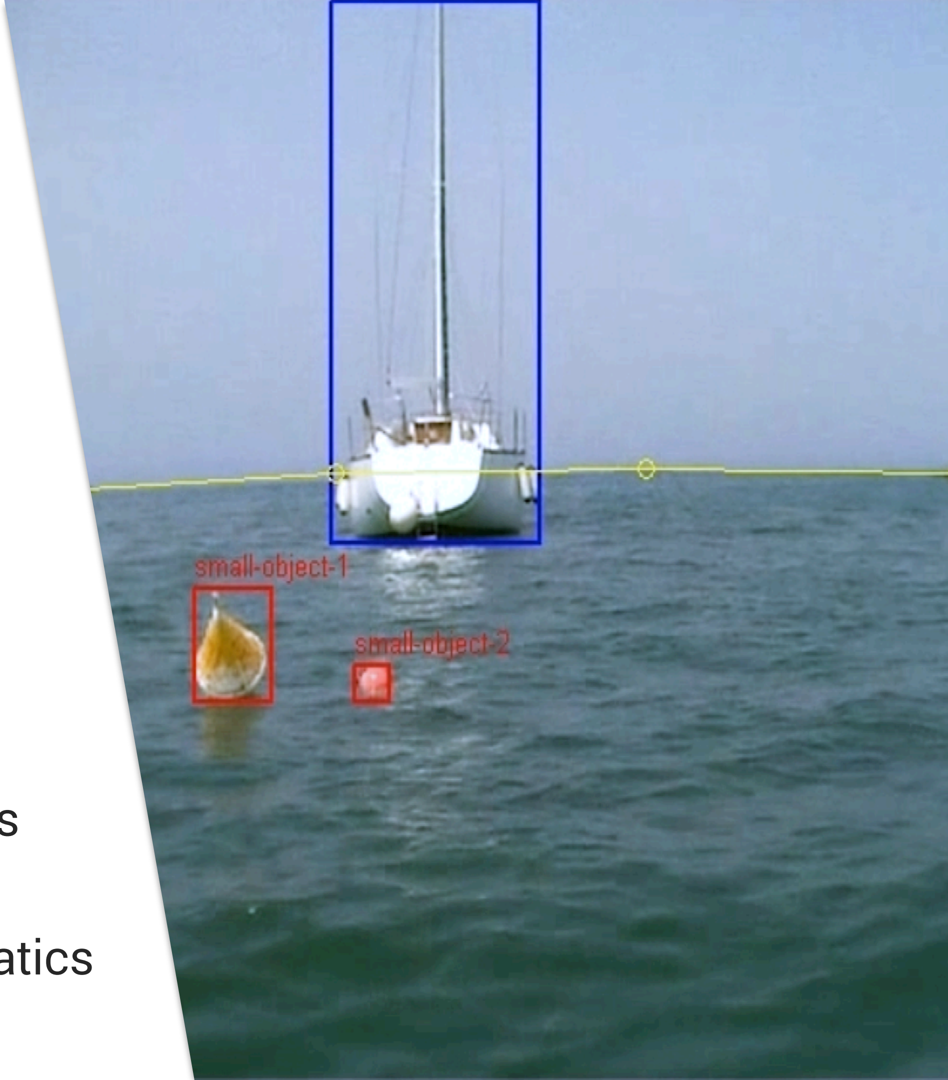
Research @ FRI

- 19 labs - a range of CS fields
- Traditionally strong in AI
  - Machine learning
  - Data mining
  - Computer vision
  - Bioinformatics
- Highlights:
  - Visual tracking challenge winners
  - Kaggle winners
  - Nature publications in bioinformatics



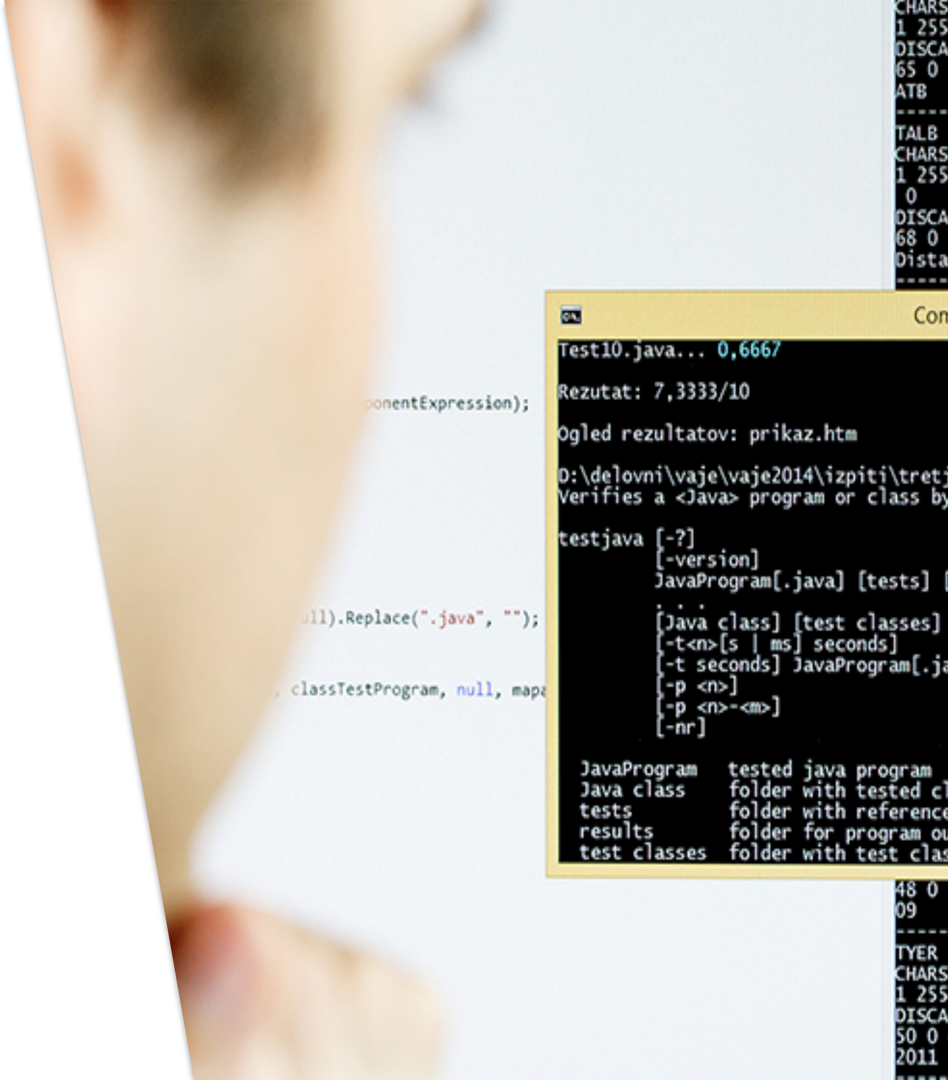
Mobile Systems Research – HCI Perspective

Mobile Notifications

- Increasingly interactive lives
  - 100 notifications/day per user
- For recipients, a means of information awareness
  - Anxious without notifications
- For senders, a way to initiate remote communication

Poor Notification Timing

- Reduced work efficiency



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Poor Notification Timing

- Reduced work efficiency
- Missed marketing opportunities

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Poor Notification Timing

- Reduced work efficiency
- Missed marketing opportunities
- Critical safety consequences

"There is more information available at our fingertips during a walk in the woods than in any computer system, yet people find a walk among trees relaxing and computers frustrating. Machines that fit the human environment instead of forcing humans to enter theirs will make using a computer as refreshing as taking a walk in the woods."

Mark Weiser, 1991

Building a system for intelligent notification scheduling

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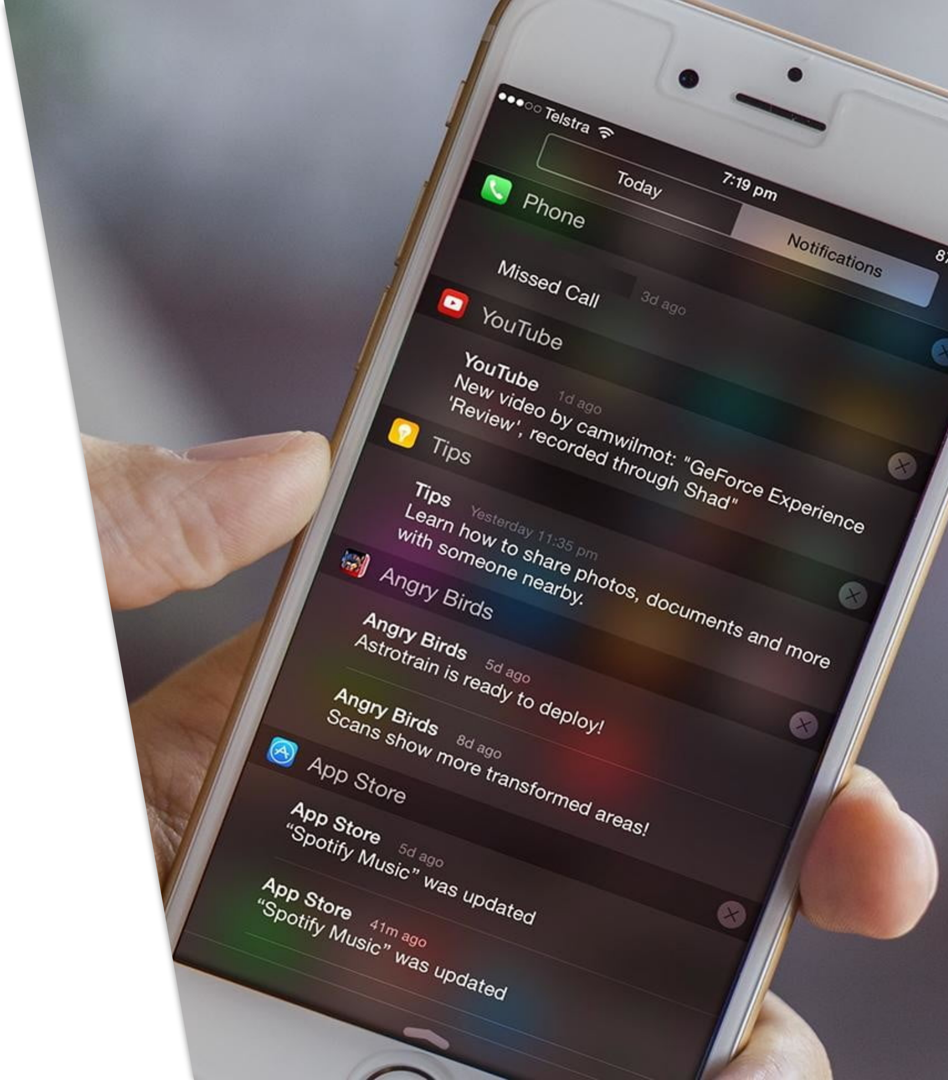
V. Pejovic and M. Musolesi
InterruptMe: Designing Intelligent Prompting Mechanisms for Pervasive Applications
UbiComp'14, Seattle, WA, USA

Towards Timely Interaction

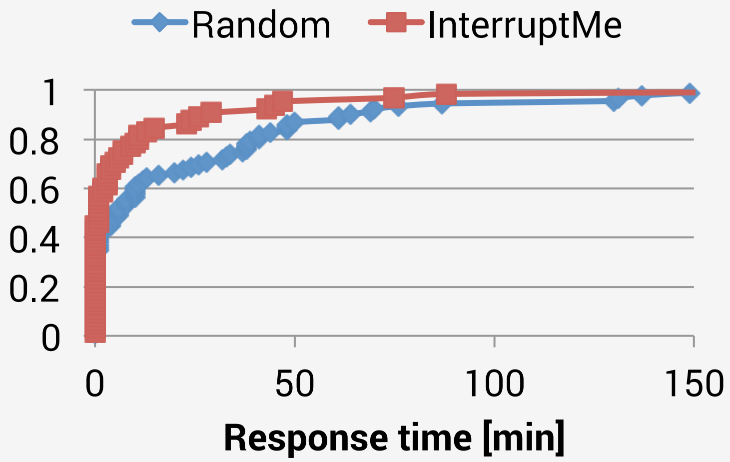
- **Premise:** notification timing is the key!
- **Path:** identify opportune moments to deliver information
- **Hypothesis:** sensed context reveals interruptibility

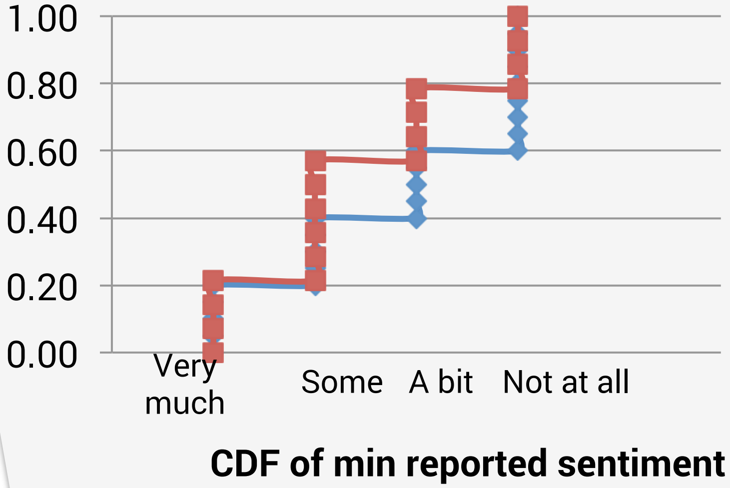


InterruptMe

- Android library for notification management
- Senses
  - accelerometer
  - location
  - time of day
- Machine learning model learns a user’s interruptibility patterns

bitbucket.org/veljkop/intelligenttrigger



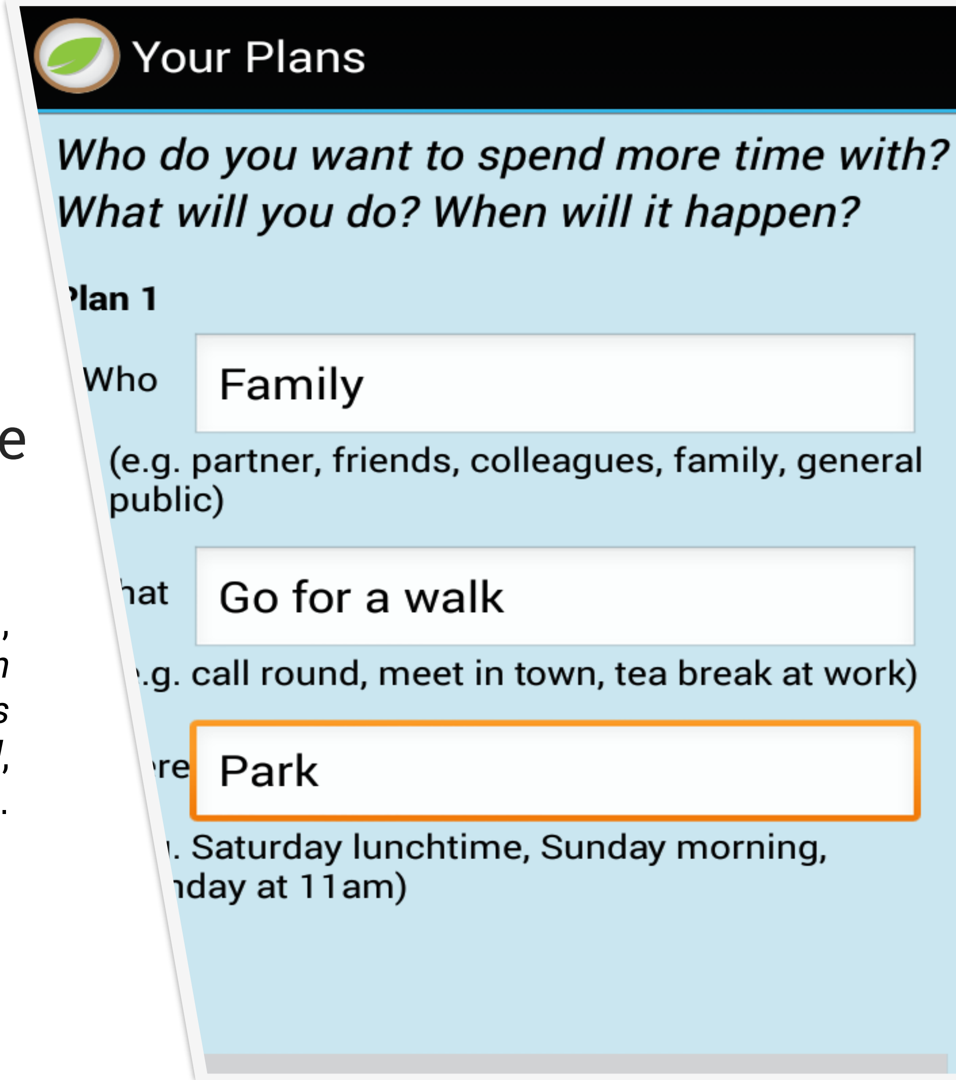


Problem solved?

Real-world Trial

- … no significant effects of notification scheduling on the usage of a behavioural change intervention app

L Morrison et al.,
The effect of timing and frequency of push notifications on usage of a smartphone-based stress management intervention: an exploratory trial,
PLoS ONE, Vol 12, (2017).



Understanding factors affecting notification acceptance

A. Mehrotra, M. Musolesi, R. Hendley and V. Pejovic

Designing Content-driven Intelligent Notification Mechanisms for Mobile Applications

UbiComp'15, Osaka, Japan, September 2015.

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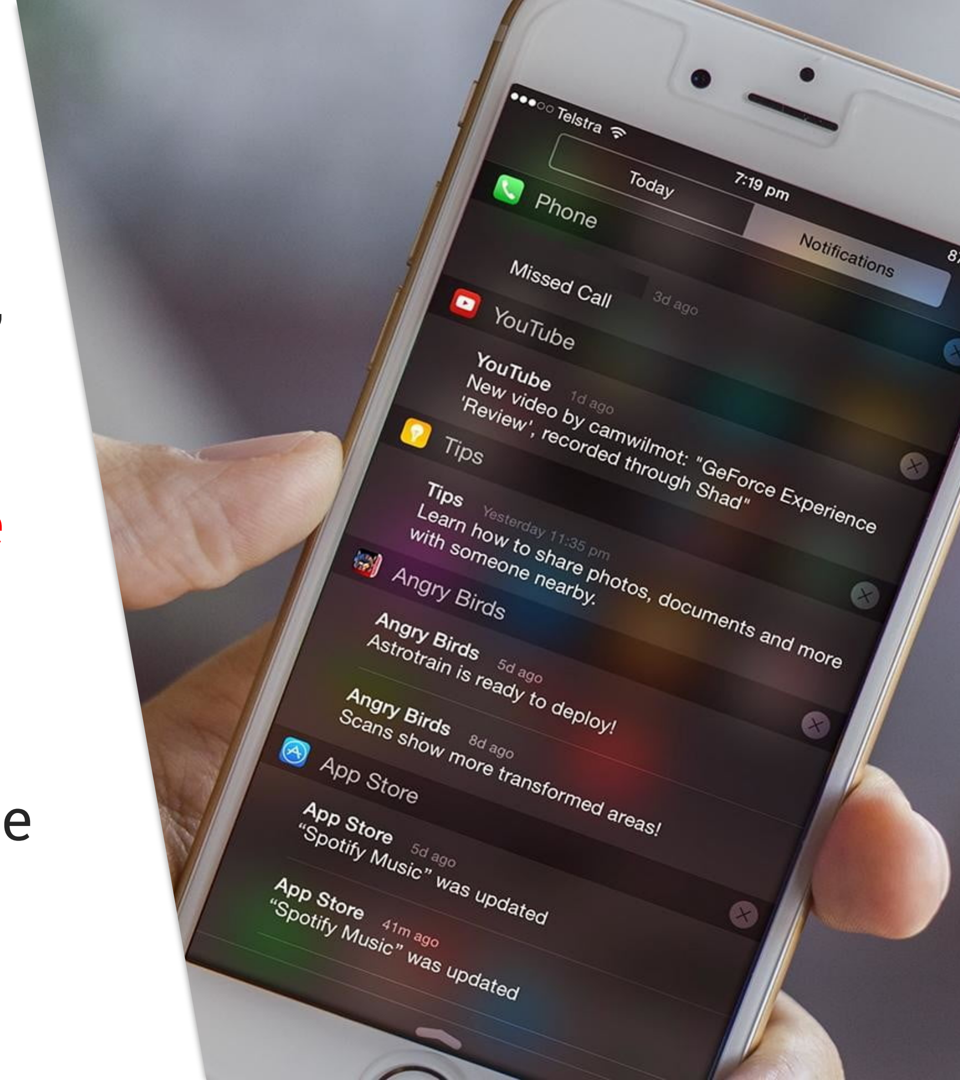
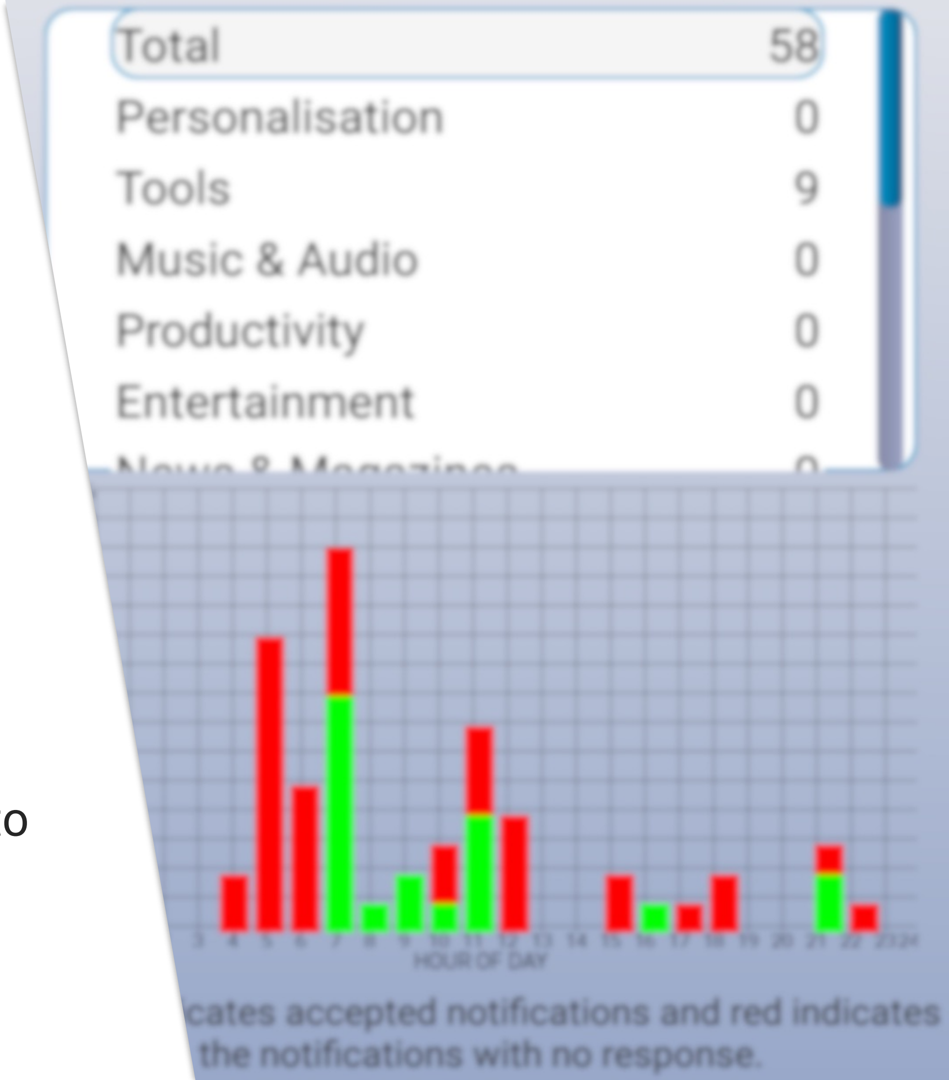
Towards Timely Interaction

- **Premise:** location, movement, and time sensing is not enough
- **Path:** monitor other on-device factors that may impact interruptibility
- **Hypothesis:** application type, content, sender, etc. determine a user’s reaction



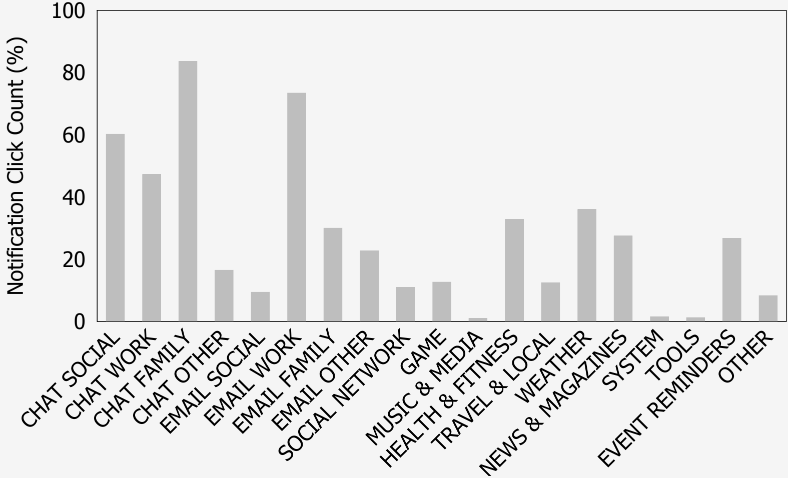
NotifyMe Mobile App

- Senses context
- Records reaction to a notification
  - Notification data
  - Category
  - Sender ID
- Gathers user preferences
  - Where and when would you like to receive notifications with similar content



Notification Reaction Analysis

- Notification click count differs between application types (i.e. content type) and sender-receiver relations



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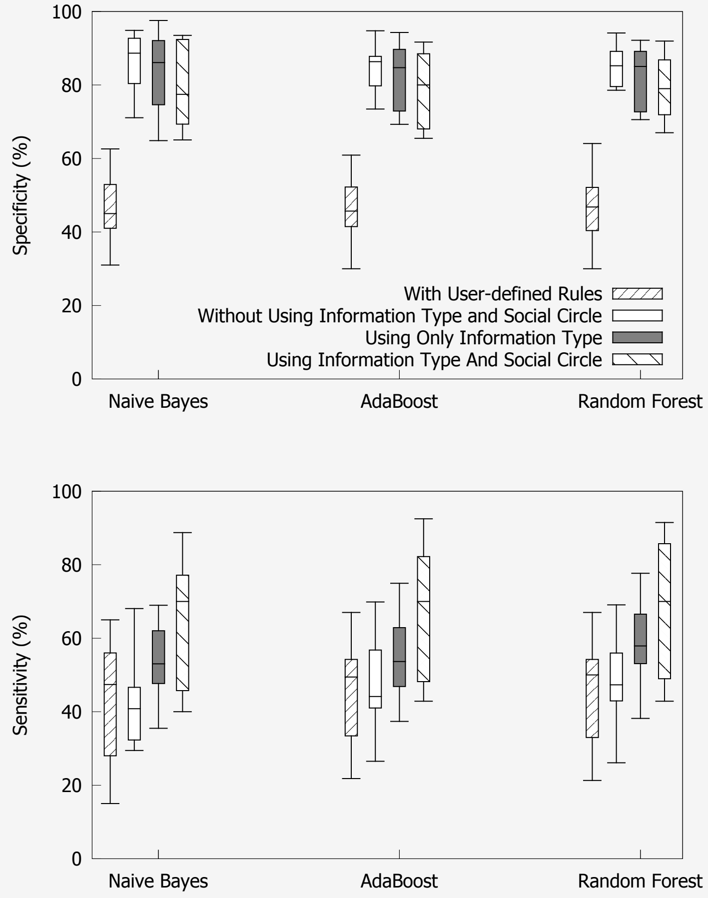
Notification Reaction Prediction

- By using information type and social circle we were able to predict the acceptance of a notification within 10 minutes from its arrival time with an average sensitivity of 70% and a specificity of 80%
- Better than user-defined rules



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User reaction does not imply user satisfaction

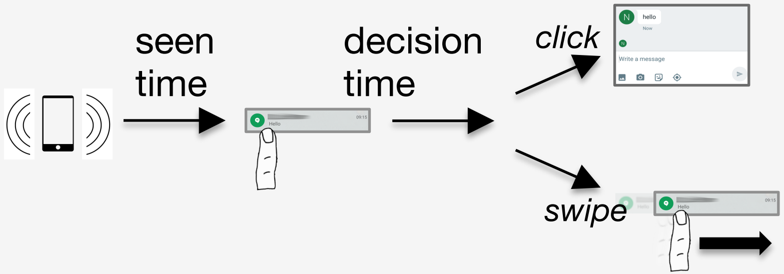
A. Mehrotra, V. Pejovic, J. Vermeulen, R. Hendley and M. Musolesi
My Phone and Me: Understanding User's Receptivity to Mobile Notifications
ACM CHI'16, San Jose, CA, USA, May 2016.

Towards Timely Interaction

- **Premise:** we identified a number of factors that impact reactions, but reactions are diverse
- **Path:** monitor users' actions and the surrounding factors
- **Hypothesis:** sensed context reveals reaction and disruption

My Phone and Me App

- Automated logging:
  - Notification time of arrival, seen, removal
  - Notification response
  - Notification details (title, app)
  - Alert type
  - Context (activity, location, etc.)
- Experience sampling:
  - Sender-receiver relationship, personality, task engagement



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Disruption Analysis

- Task complexity and interruptibility:
  - More disruptive if it arrives when the user is in the middle of or finishing a task
  - Perceived disruption increases with the complexity of an ongoing task
  - Faster to react if engaged in a complex task

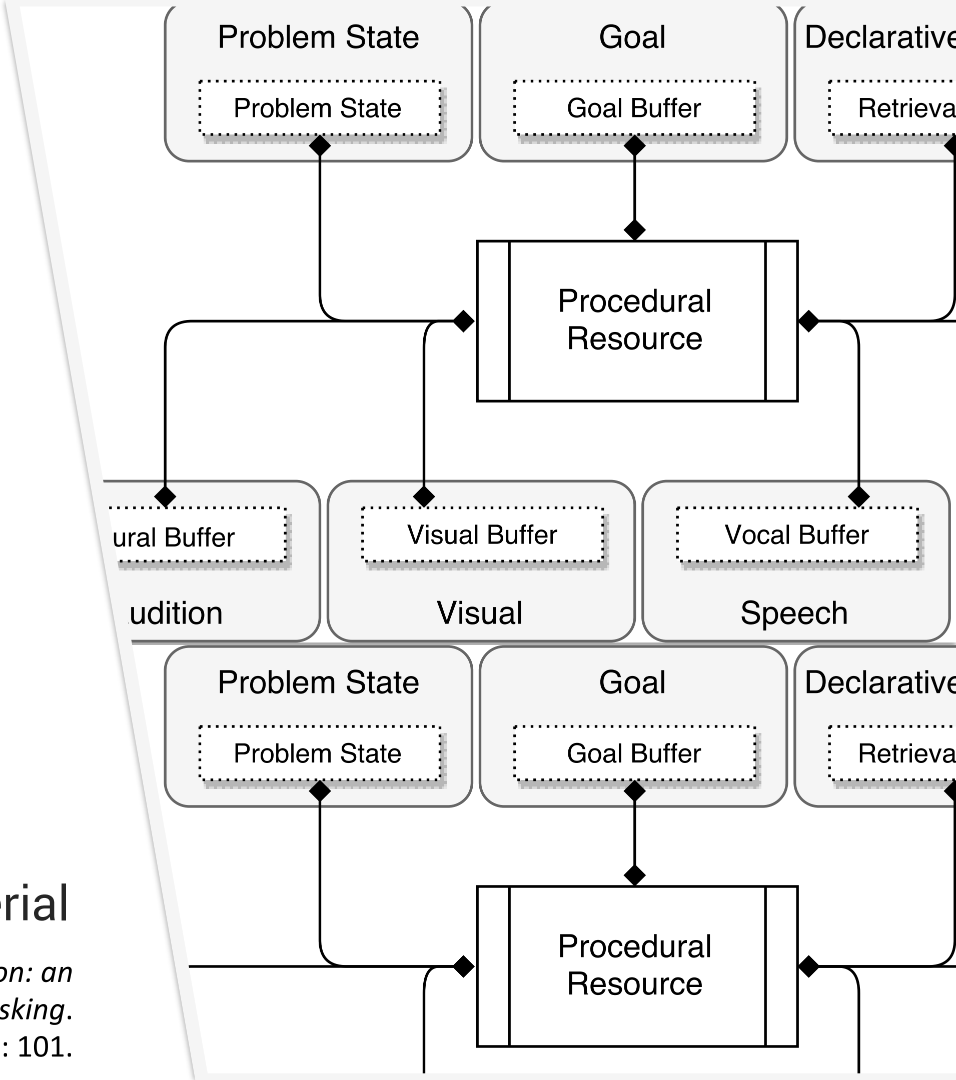
Also confirmed:

Pejovic et al., "Investigating The Role of Task Engagement in Mobile Interruptibility", Smarttention workshop with Ubicomp'15

How does a thought get disrupted?

Theory of Multitasking

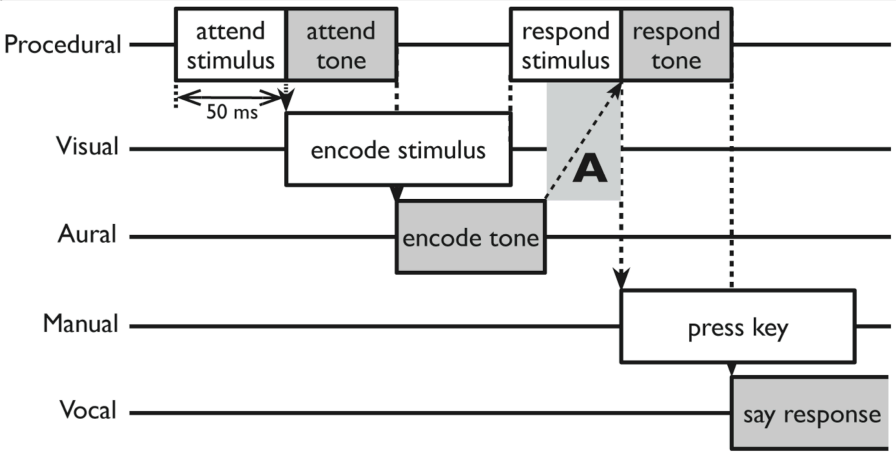
- Resources:
  - Perceptual and motor
  - Cognitive
    - Procedural memory
    - Declarative memory
- Mechanisms:
  - Resource use is exclusive – one task at a time per resource
  - Multiple problem threads run in parallel, but processing is still serial



Salvucci and Taatgen. *Threaded cognition: an integrated theory of concurrent multitasking*. Psychological review 115.1 (2008): 101.

Theory of Multitasking

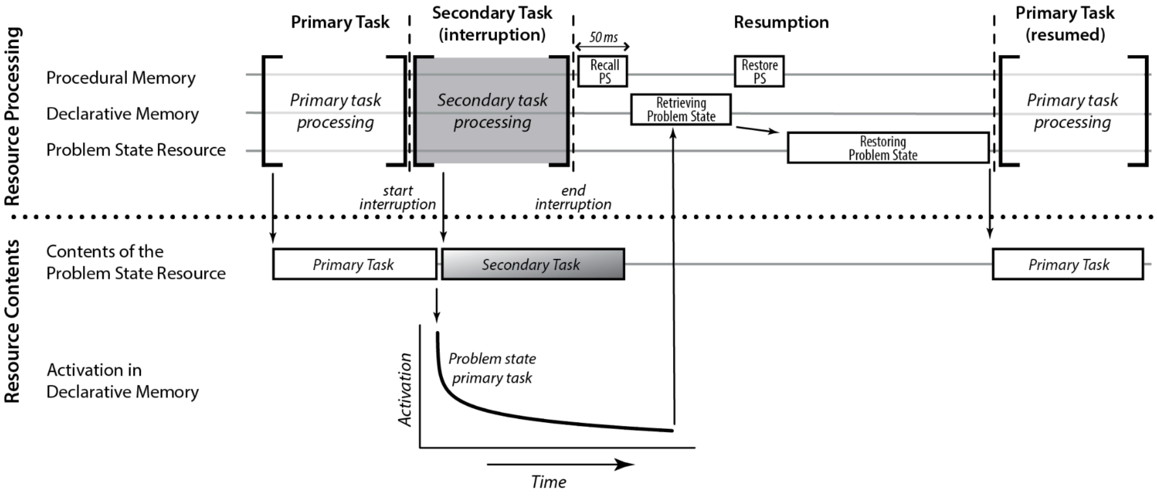
- Interference when two or more threads ask for the same resource at a time



Borst et al.
The problem state: a cognitive bottleneck in multitasking.
Journal of Experimental Psychology: Learning, memory, and cognition 36.2 (2010): 363.

Theory of Multitasking

- Complex tasks require problem state saving/retrieving



Borst et al.
What Makes Interruptions Disruptive?: A Process-Model Account of the Effects of the Problem State Bottleneck on Task Interruption and Resumption.
CHI'15, 2015.

Implications on Mobile Attention Management

- Interruptions are more disruptive if they require problem state switching

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Implications on Mobile Attention Management

- Make them less disruptive by interrupting:
  - At moments when a task is not fully active (e.g. just starting, or just finished)
  - At moments when a task does not require a problem state
  - At moments when a user is working on a task that is well practiced, a routine


"Mr. Osborne, may I be excused? My brain is full."

Can we automatically infer task engagement with smartphones?

G. Urh and V. Pejovic,
TaskyApp: Inferring Task Engagement via Smartphone Sensing
Ubittention workshop with ACM UbiComp'16, Heidelberg, Germany.

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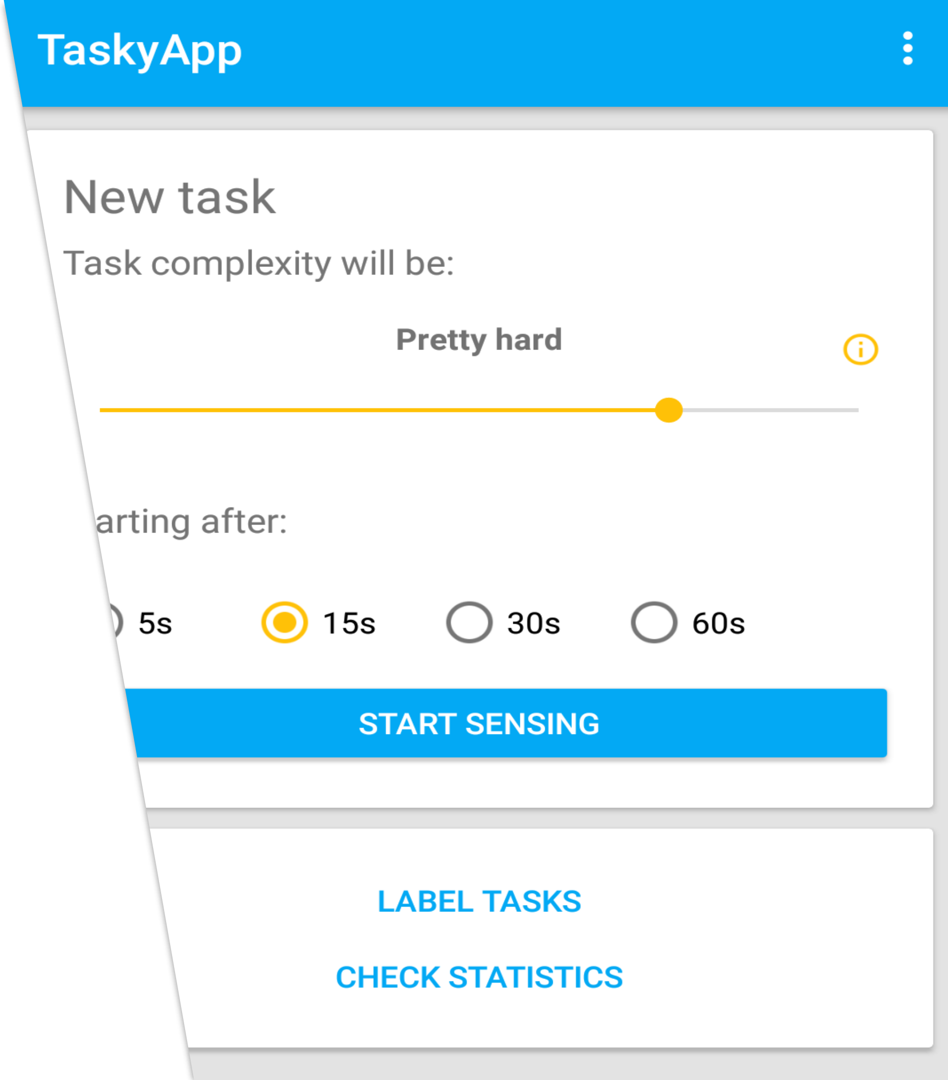
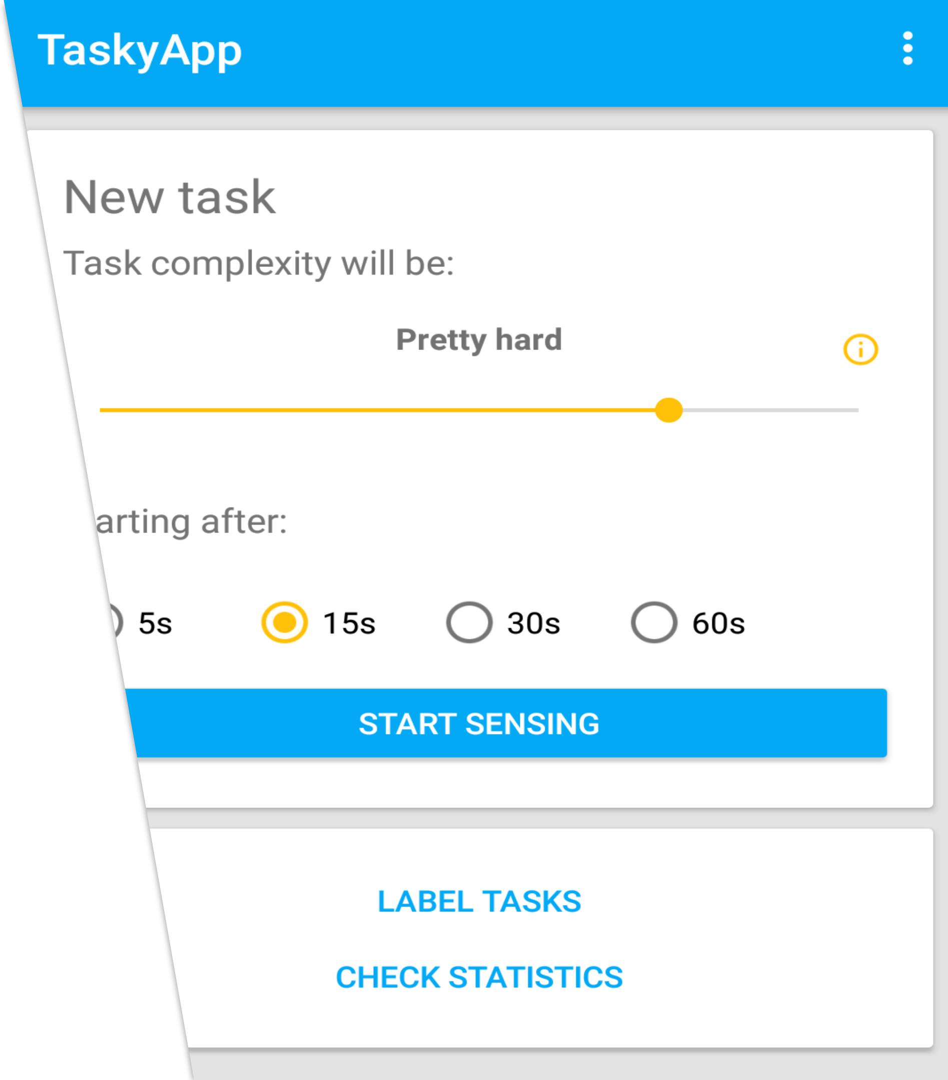
TaskyApp

- Background sensing of device movement, ambient sound, collocation with other devices
- Data labelling via experience sampling and retroactive assisted labelling



TaskyApp

- Recruited eight office workers for five weeks
  - 232 labelled instances (3035 unlabelled)
  - Most data between 8am and 6pm



Data Analysis

- Linear regression (N=232) fit with sensed features as independent variables and task difficulty (1-5) as a dependent variable
  - Movement data gives the most informative features
  - The regression explains only a small part of the data (R^2=0.19)

Variable	Coefficient	t (sig.)
Acc. Y-axis mean	-.038	-1.84 (.068)
Acc. Z-axis mean	.026	1.43 (.153)
Gyro. mean intensity crossing rate	0.003	4.06 (.000)
Gyro. intensity variance	0.200	1.24 (.217)
Hour of day	.067	3.49 (.001)
Majority	0.5	0.5

Data Analysis

- Classify a task engagement moment as either "easy" or "difficult" depending on the sensed features
  - We experimented with different classifiers but Naïve Bayes seems to work best (probably due to the low amount of data)
    - 62.5% accuracy (52.8% baseline)
    - "Favourable" errors

EASY'	DIFFICULT'	
45 (19.4%)	62 (26.7%)	EASY
25 (10.8%)	100 (43.1%)	DIFFICULT

Can we automatically infer task engagement with wearables?

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M. Gjoreski, M. Luštrek and V. Pejović,
My Watch Says I'm Busy: Inferring Cognitive Load with Low-Cost Wearables
Ubittention workshop with ACM UbiComp'18, Singapore.

Physiological Signals for Cognitive Load Inference

- **Premise:** heart rate (variability), electrodermal activity, pupil dilation, EEG changes correlate with CL changes
- **Path:** low-cost wearable sensing devices can capture signals ~ cognitive load
- **Hypothesis:** ML on these data to infer cognitive load

Collected Data

- Preliminary data:
  - Demographics
  - Cognitive capacities (N-back test)
  - Personality (Hexaco) test

Collected Data

- Primary (PC-based) task
  - Adapted from Haapalainen et al.
  - Six task types, each with three difficulty levels
  - NASA TLX after each task
- Physiological measurements
  - Heart rate intervals (R-R), galvanic skin response (GSR) and skin temperature (ST)
- Secondary task

Experiment

Part 1	Demographic Questionnaire	2-back task	3 minutes Rest	3-back task	3 minutes Rest	Personality Questionnaire

Part 2	P-task n Intensity x S-task	Task load Quest. + Rest	P-task n Intensity x S-task	Task load Quest. + Rest	P-task n Intensity x S-task	Task load Quest. + Rest	3 minutes Rest	6 cycles

- Demographics:
  - 25 users (21 completed successfully)
  - 20-58 years old
  - 5 female

Data Overview

- Extracted 81 physiological, demographic, cognitive capacity, and personality features
- Predicting three CL measures:
  - TLX (subjective)
  - Opacity (sec. task performace)
  - Task label (objective)

P-Task	(μ±δ)TLX	(μ±δ)Opacity	r(TLX-DTD)	r(TLX-Opacity)	r(DTD-Opacity)
HP	13.8 ± 4.7	0.1 ± 0.04	0.34	-0.01	0.13
FA	17.9 ± 7.8	0.1 ± 0.03	0.16	-0.08	0.07
GC	17.4 ± 6.1	0.1 ± 0.06	0.48	-0.06	-0.05
NC	17.7 ± 7.7	0.08 ± 0.03	0.34	-0.14	-0.01
SX	17.1 ± 7.7	0.12 ± 0.1	0.40	-0.21	-0.33
PT	17.4 ± 9.0	0.14 ± 0.16	0.43	-0.08	-0.27
Overall	16.9 ± 7.4	0.1 ± 0.08	0.34	-0.09	-0.13

Secondary task shows very weak correlation with TLX or DTD

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Cognitive Load Prediction

- Cast into classification task
- Classifiers: Naïve Bayesian, Random Forest, Gradient Boosting, AdaBoost, SVM, KNN, Trees
- Modestly better than the baseline
- Confuses neighbouring difficulties

Target	µ Majority	Best model	Best model µ Accuracy	Accuracy increase relative to Majority						
				HP	FA	GC	NC	SX	PT	µ
TLX	40%	RF	47%	6%	-5%	5%	6%	21%	10%	7%
DTD	33%	NB	51%	27%	11%	10%	22%	14%	24%	18%
Opacity	36%	GB	46%	16%	5%	13%	6%	3%	20%	10%

	Easy	Medium	Difficult
Easy	158	101	65
Medium	98	163	63
Difficult	69	91	164
Precision	49%	46%	56%
Recall	49%	50%	51%
F1	49%	48%	53%
Accuracy		51%	

Fully unobtrusive task engagement inference

T. Matkovič and V. Pejović,
Wi-Mind: Wireless Mental Effort Inference
Ubittention workshop with ACM UbiComp'18, Singapore.

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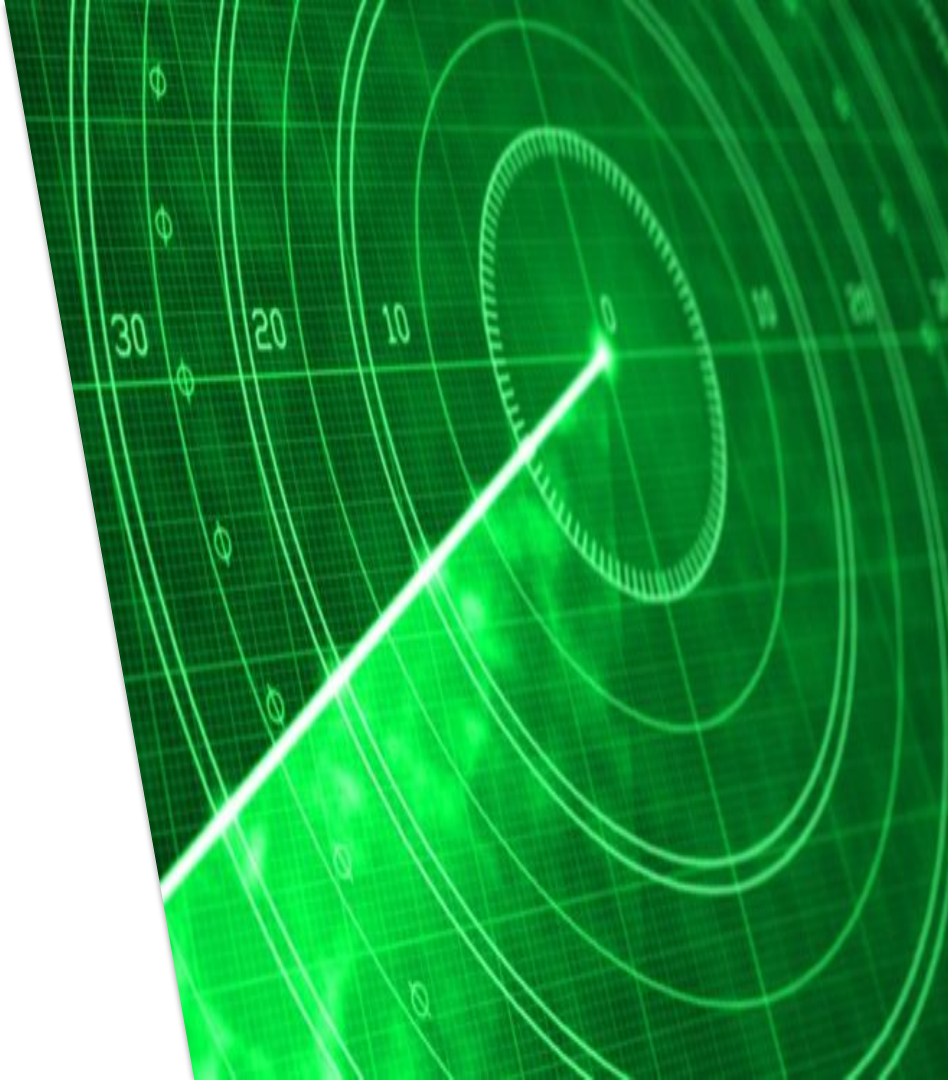
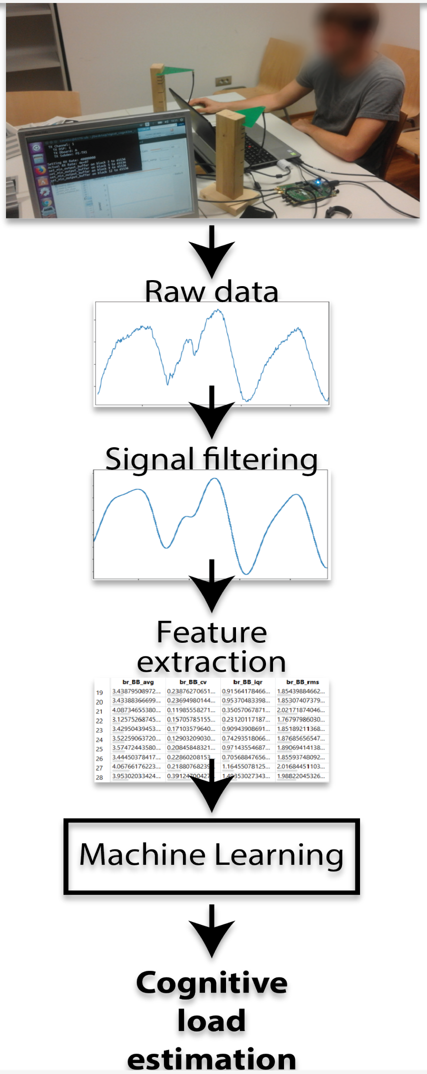
Wireless Cognitive Load Inference

- **Premise:** radar can detect breathing and heart beat related body movement
- **Path:** custom radar
- **Hypothesis:** filtered radar signals as a basis for ML models of CL



Wi-Mind

- Software-Defined Radio (SDR) implementation of FMCW radar followed by phase analysis
- Monitor movement as a user is solving tasks of different difficulty
- Extract heart beat and breathing-related features
- Build ML models



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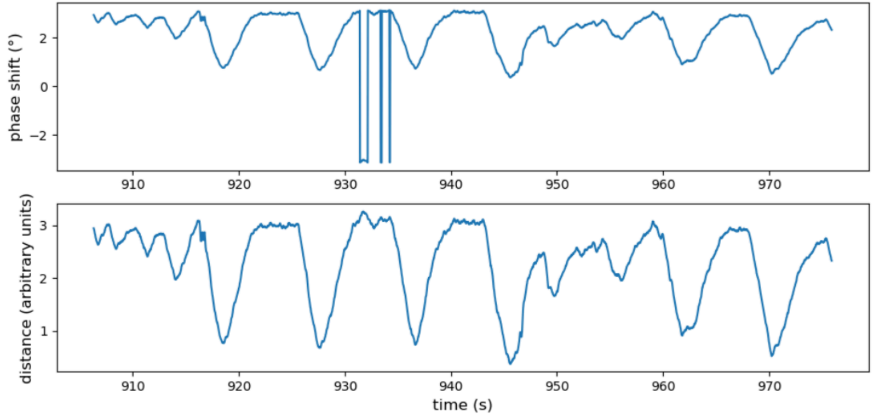
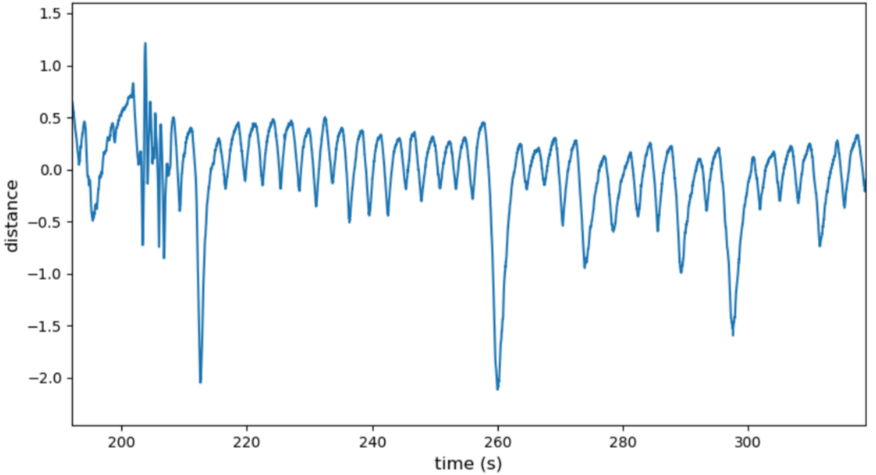
From EM Waves to Physiological Signals

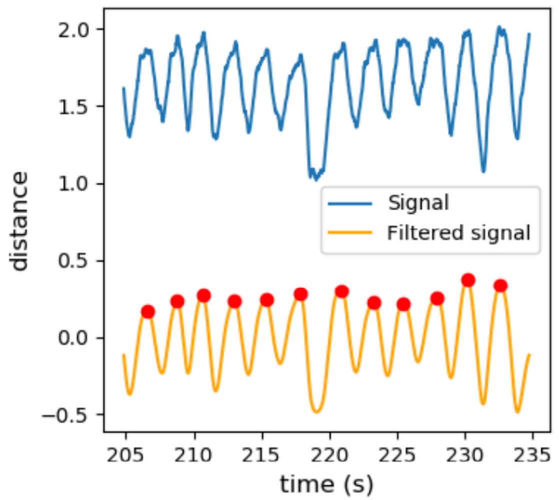
- Preprocessing:
  - Unwrapping phase
  - Filtering HF and LF noise

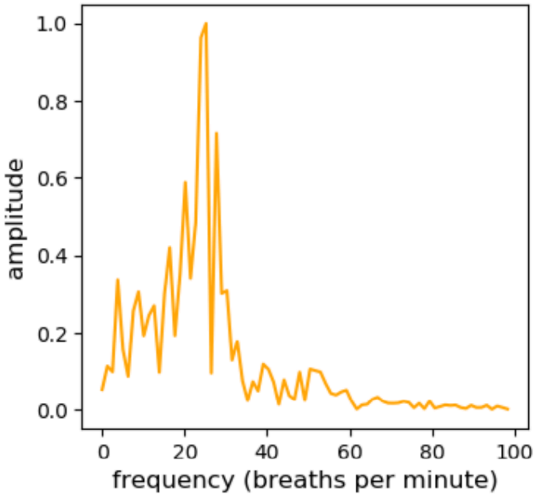




From EM Waves to Physiological Signals

- Preprocessing:
  - Unwrapping phase
  - Filtering HF and LF noise
- Extracting breathing signal
  - Breathing rate (via FFT) features: mean rate, power in different bands, etc.
  - Inter-breath features (peak detection): avg. interval, variation, I:E, etc.
- Metafeature
  - Is the signal “clean”?





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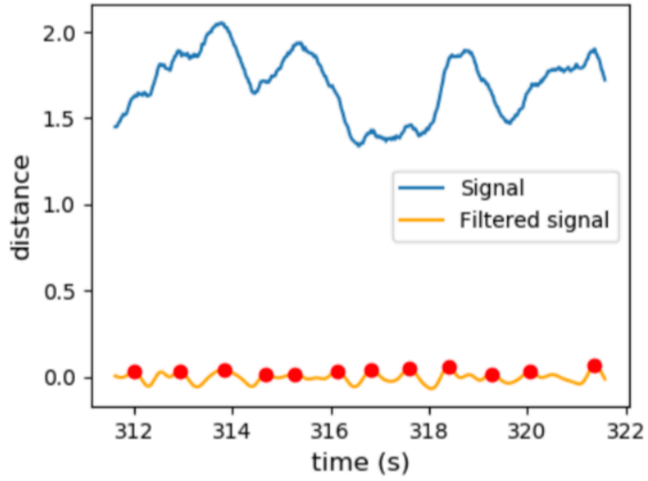
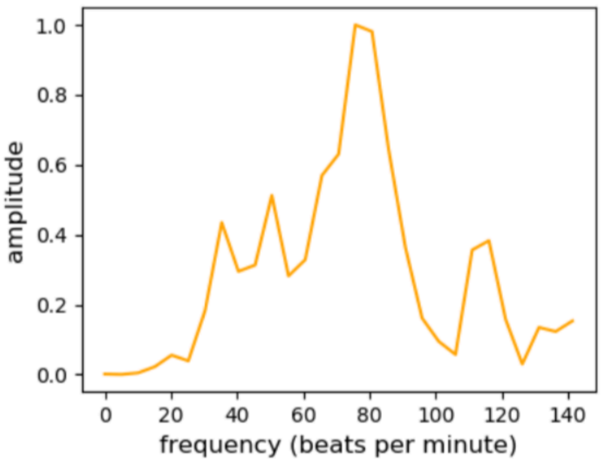
From EM Waves to Physiological Signals

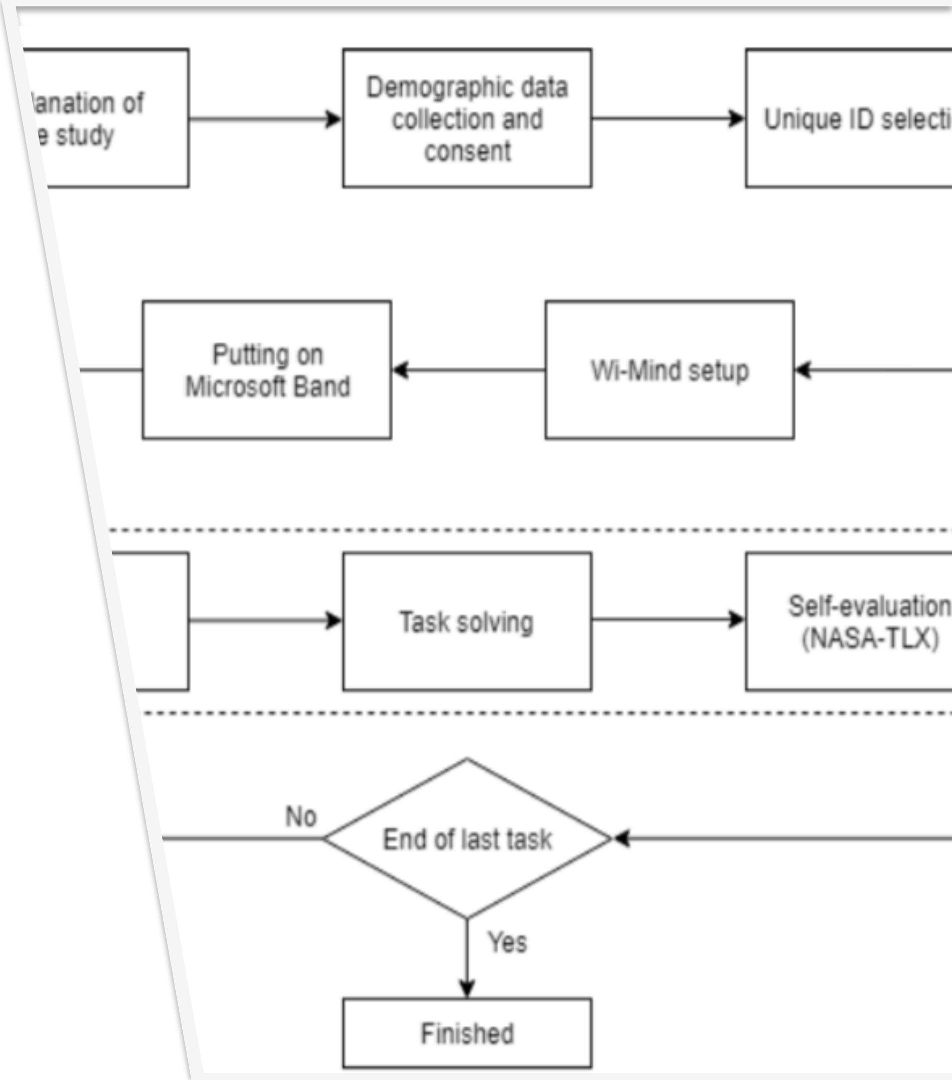
- Preprocessing:
  - Unwrapping phase
  - Filtering HF and LF noise
- Extracting heart beat signals:
  - Heart rate (FFT)
  - Heart rate variability HRV (peak detection + filtering) features: RR intervals, LF and HF HRV





WiMind Experiments

- Primary (PC-based) task
  - Adapted from Haapalainen et al.
  - NASA TLX after each task

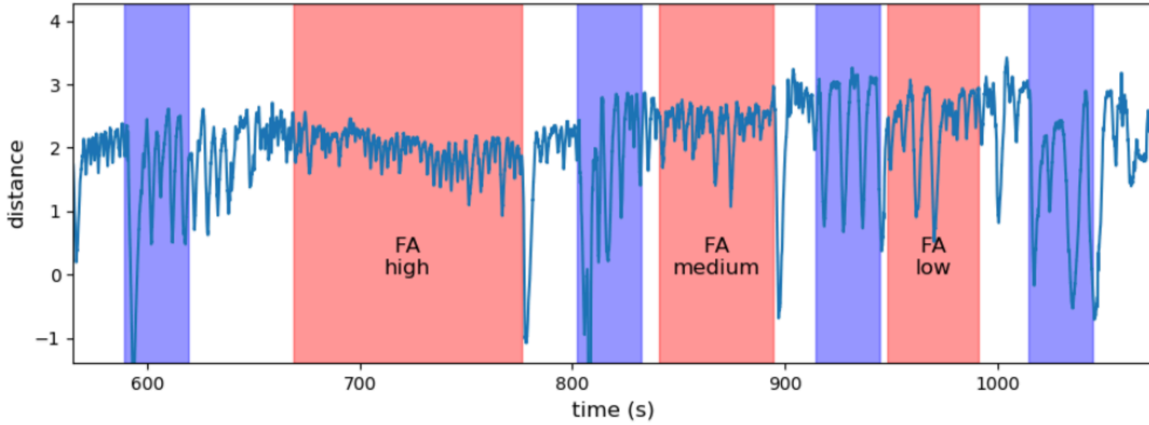


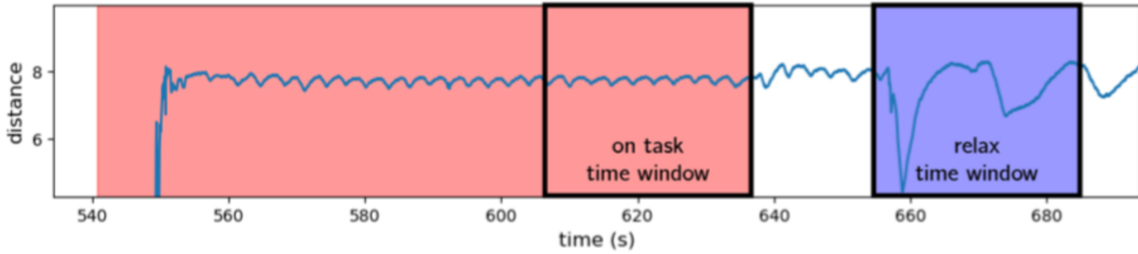
WiMind Experiments

- Primary (PC-based) task
  - Adapted from Haapalainen et al.
  - NASA TLX after each task
- WiMind wireless measurements
- MS Band + Android app
- Demographics
  - 23 users
  - 20-38 years old
  - 6 female, 17 male

Results

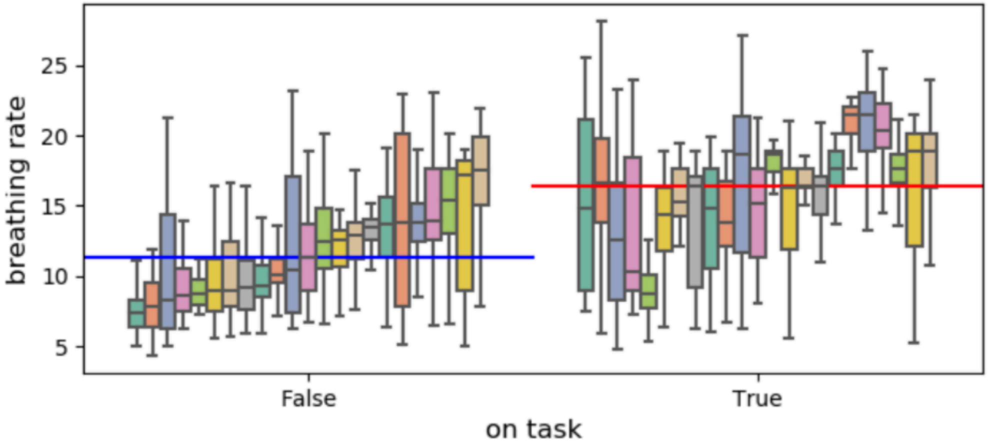
- Labelling signals via time windows:
  - Last 30 seconds of task engagement (label “busy”)
  - 30 seconds of explicit relaxation (label “relax”)



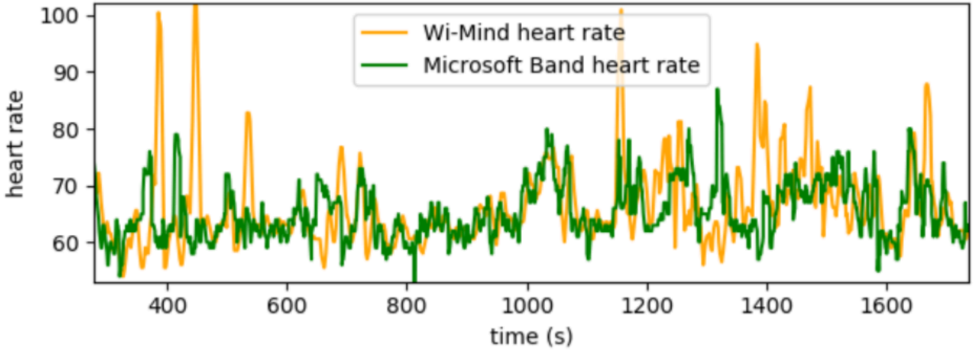


But first…

- Breathing rate validation



- Heart rate validation



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Inferring Task Engagement (Binary)

- Normalised breathing rate
- Different ML models from the “standard” toolbox
- Leave-one-person-out validation

Method	**AUC**	**Accuracy**
k-NN	0.752	0.704
SVM	0.670	0.580
Random forest	0.806	**0.746**
Naïve Bayes	0.780	0.723
Majority	0.5	0.5

Inferring Task Engagement (Binary)

- Normalised breathing rate
- Different ML models from the "standard" toolbox
- Leave-one-person-out validation
- Personalised models improve performance for some users but overall no improvement

Method	Accuracy
k-NN	0.604
SVM	0.721
Random forest	0.721
Naïve Bayes	**0.734**
Majority	0.5

Inferring Task Engagement (E/M/H)

- Unable to distinguish among different complexity levels
- Results are better if we consider only Easy and Hard tasks
- Linear regression for TLX gives similarly poor results

Method	Accuracy
k-NN	0.343
SVM	0.328
Random forest	**0.369**
Naïve Bayes	0.337
Majority	0.34

Neural Network Approach

- Long Short-Term Memory (LSTM) neural network
- Raw wireless phase signal
- Accuracy results:
  - Binary (busy/relaxed): **0.752** (vs 0.5 majority; 0.746 random forest)
  - No improvement with tertiary (E/M/H) or task-specific models

Towards (very accurate) unobtrusive cognitive load inference

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Summary

- (Relatively) successfully detect whether a person is engaged in a task or not even with WiMind
- Detecting the level of engagement is challenging even with direct sensing with off-the-shelf wearables
- Secondary task (the way we designed it) is not a reliable proxy for task complexity or TLX

Expanding Our Approach

- The role of personality traits
- Heterogeneous data sources:
  - Phone: accelerometer, calendar info, screen on/off
  - Wristband: HR(V), GSR, accelerometer, barometer, UV
  - Wireless: breathing, HR(V)
- Task types that elicit the strongest physiological response

Research Directions

- Which type of cognitive load can/should we detect:
  - Intrinsic
  - Extraneous
  - Germane
- Should we infer objective or subjective task difficulty?

Collaboration Opportunities

- Real-world applications
- Research projects
  - Horizon Europe, etc.
- Erasmus+ exchanges for
  - PhD students (up to three months)
  - Staff
- Join us as a doctoral student!

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Submit to our conference!

- Human-Computer Interaction in Information Society HCI-IS 2019 conference
  - http://hci.si/hci-is-2019/

Collaborators

- WiMind:
  - Tilen Matkovic, Uni. of Ljubljana
- Wearables:
  - Martin Gjoreski, Mitja Lustrek, Institut Jozef Stefan, Ljubljana
- TaskyApp:
  - Gasper Urh, Uni. of Ljubljana
- Mobile Interruptibility:
  - Mirco Musolesi, Abhinav Mehrotra, University College London
  - Christoph Anderson, University of Kassel

Thank You!

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Find out more:
"A Survey of Attention Management Systems in Ubiquitous Computing Environments" by Anderson et al., ACM IMWUT (Ubicomp) 2018

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