Cognitive Load Inference for Ubiquitous Computing Adaptation

Credit: Shutterstock.com

Master studies, 2021/2022

Dr Veljko Pejović
Veljko.Pejovic@fri.uni-lj.si

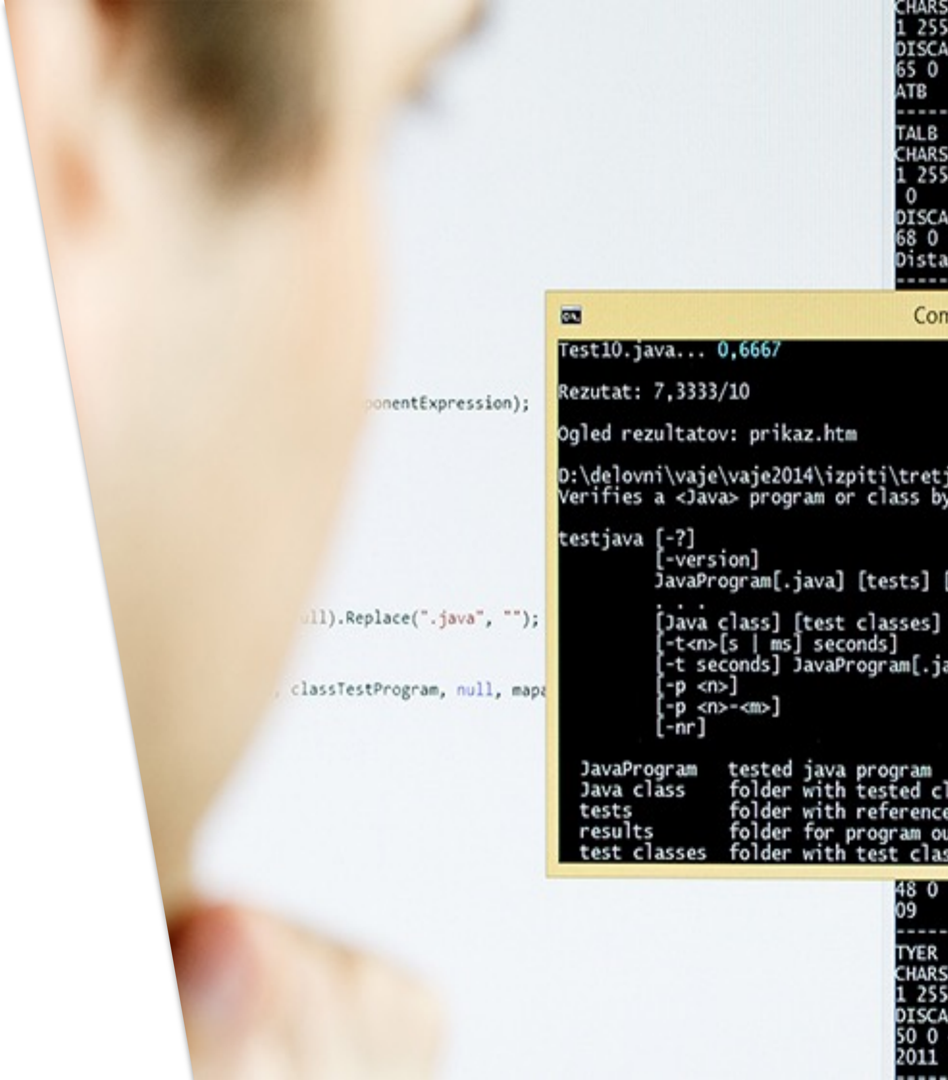
University of Ljubljana
Faculty of Computer and Information Science

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

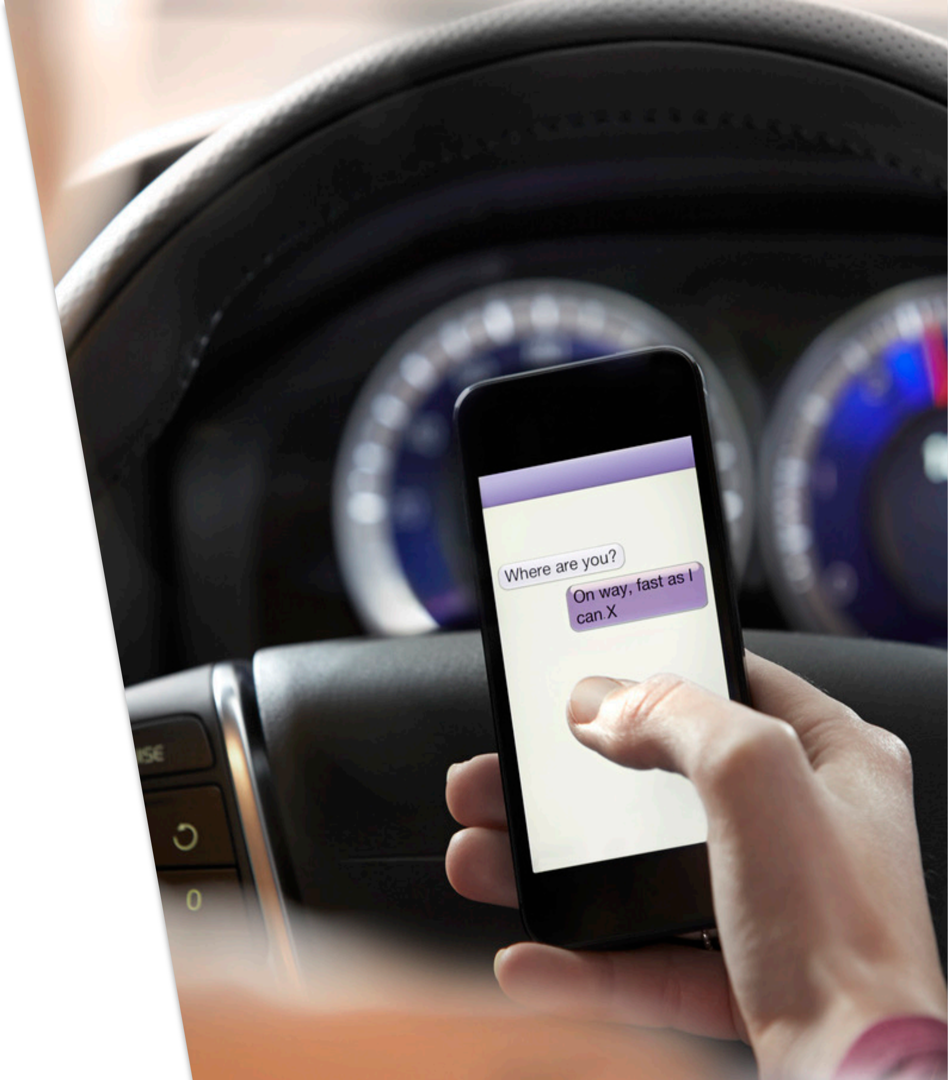


Poor Notification Timing

- Reduced work efficiency
- Missed marketing opportunities

Poor Notification Timing

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



University of Ljubljana
Faculty of Computer and Information Science

"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

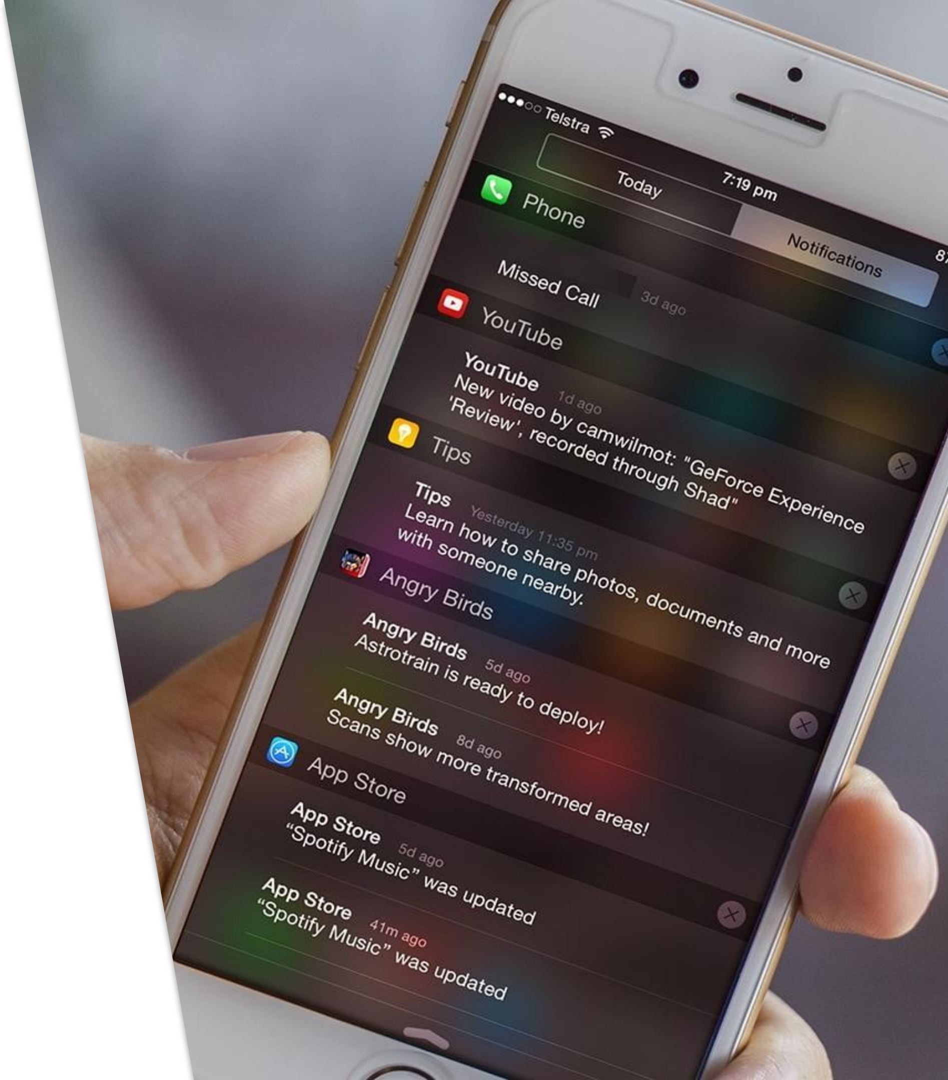
Building a system for intelligent notification scheduling

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

University of Ljubljana
Faculty of Computer and Information Science

Towards Timely Interaction

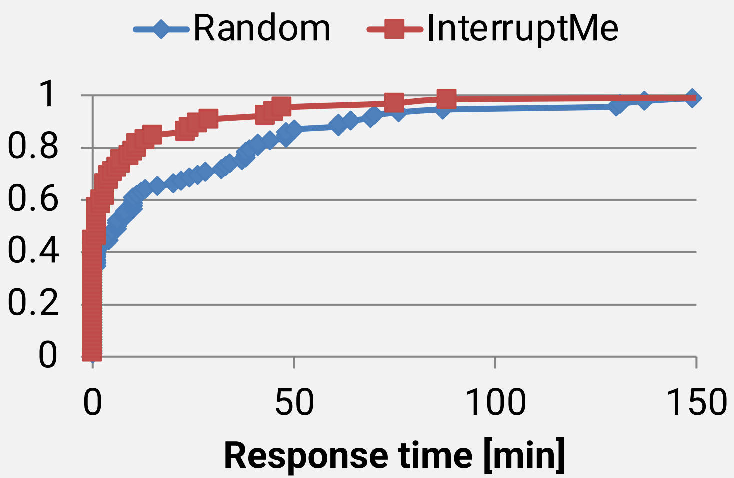
- **Premise:** notification timing is the key!
- **Path:** identify opportune moments to deliver information
- **Hypothesis:** sensed context reveals interruptibility

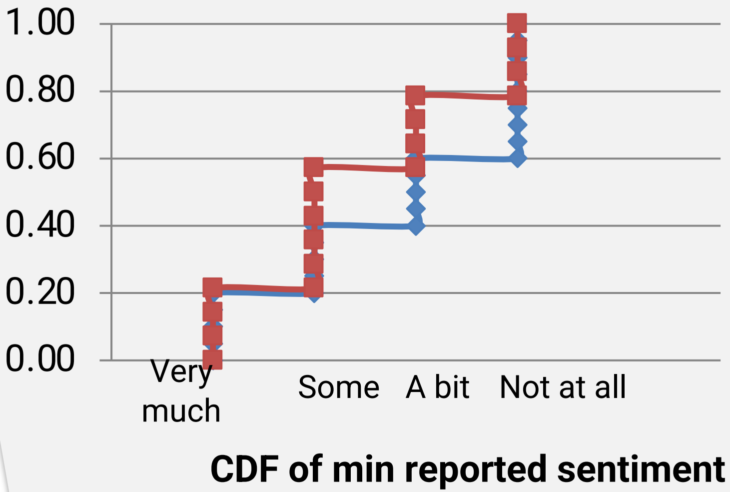


InterruptMe

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

bitbucket.org/veljkop/intelligenttrigger





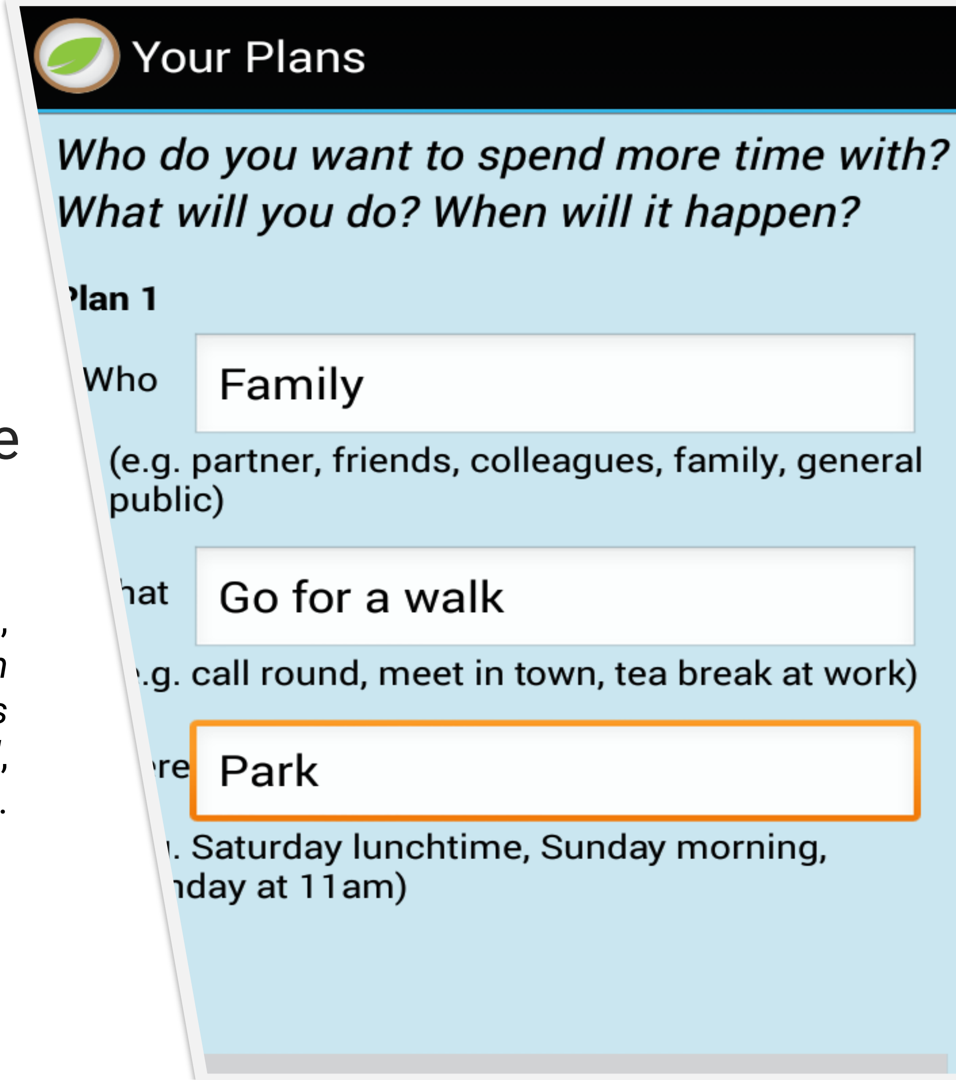
University of Ljubljana
Faculty of Computer and Information Science

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.

University of Ljubljana
Faculty of Computer and Information Science

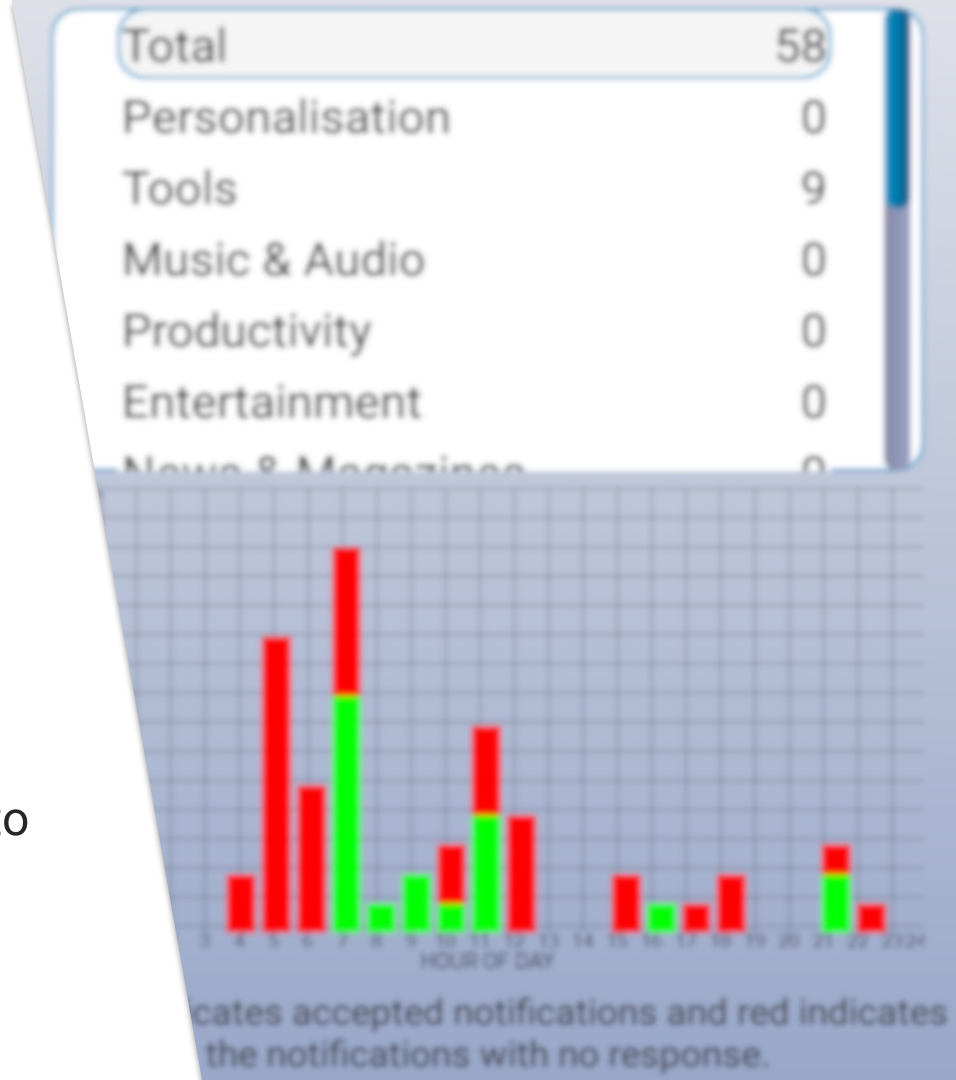
Towards Timely Interaction

- **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

University *of Ljubljana*
Faculty *of Computer and Information Science*

NotifyMe Mobile App

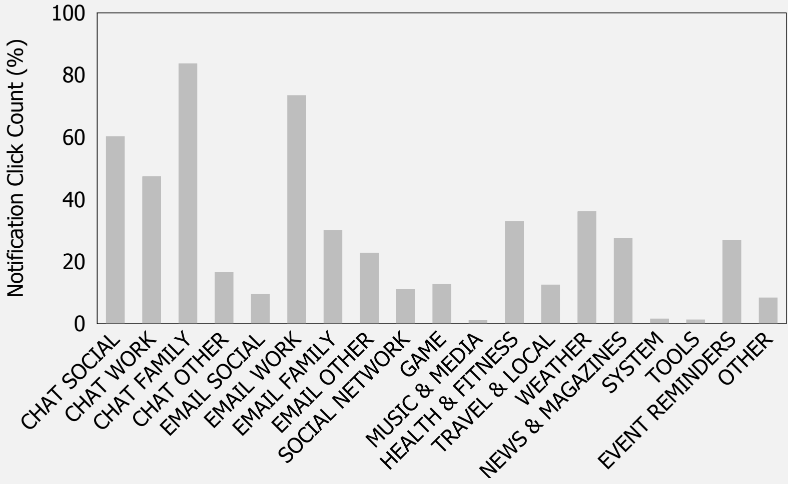
- Senses context
- Records reaction to a notification
  - Notification data
  - Category
  - Sender ID
- Gathers user preferences
  - Where and when would you like to receive notifications with similar content



University of Ljubljana
Faculty of Computer and Information Science

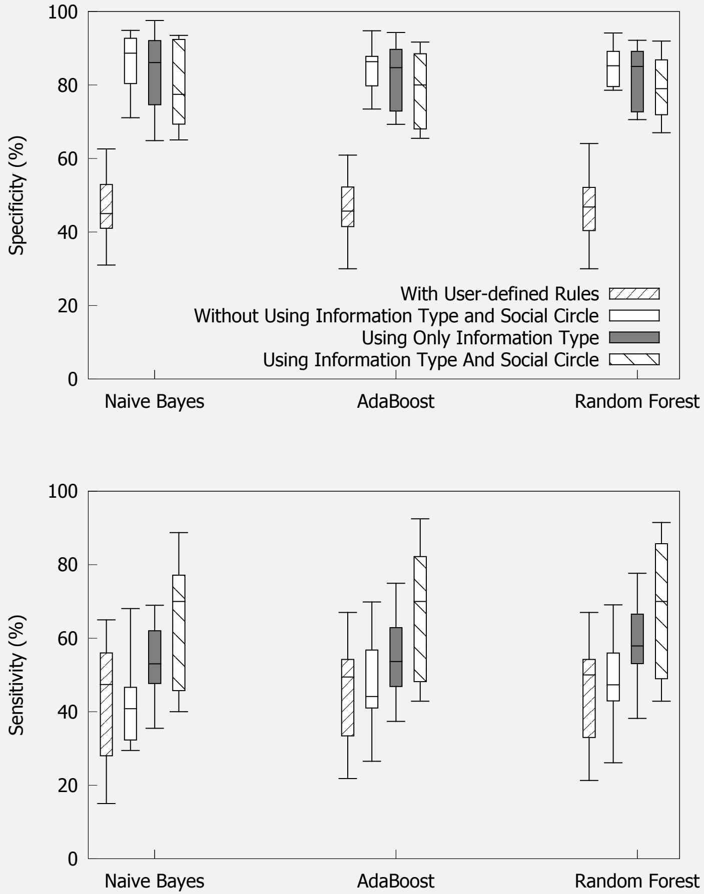
Notification Reaction Analysis

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



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



University of Ljubljana
Faculty of Computer and Information Science

User reaction does not imply user satisfaction

University *of Ljubljana*
Faculty *of Computer and Information Science*

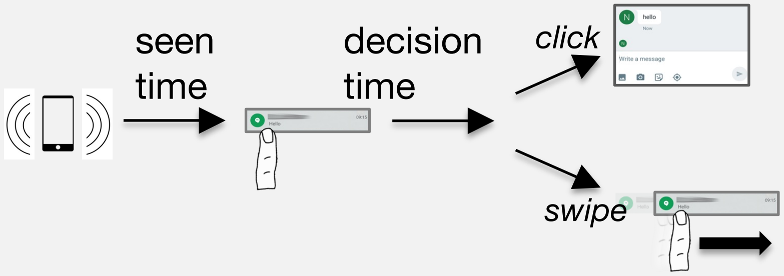
A. Mehrotra, V. Pejovic, J. Vermeulen, R. Hendley and M. Musolesi
My Phone and Me: Understanding User's Receptivity to Mobile Notifications
ACM CHI'16, San Jose, CA, USA, May 2016.

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



University of Ljubljana
Faculty of Computer and
Information Science

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

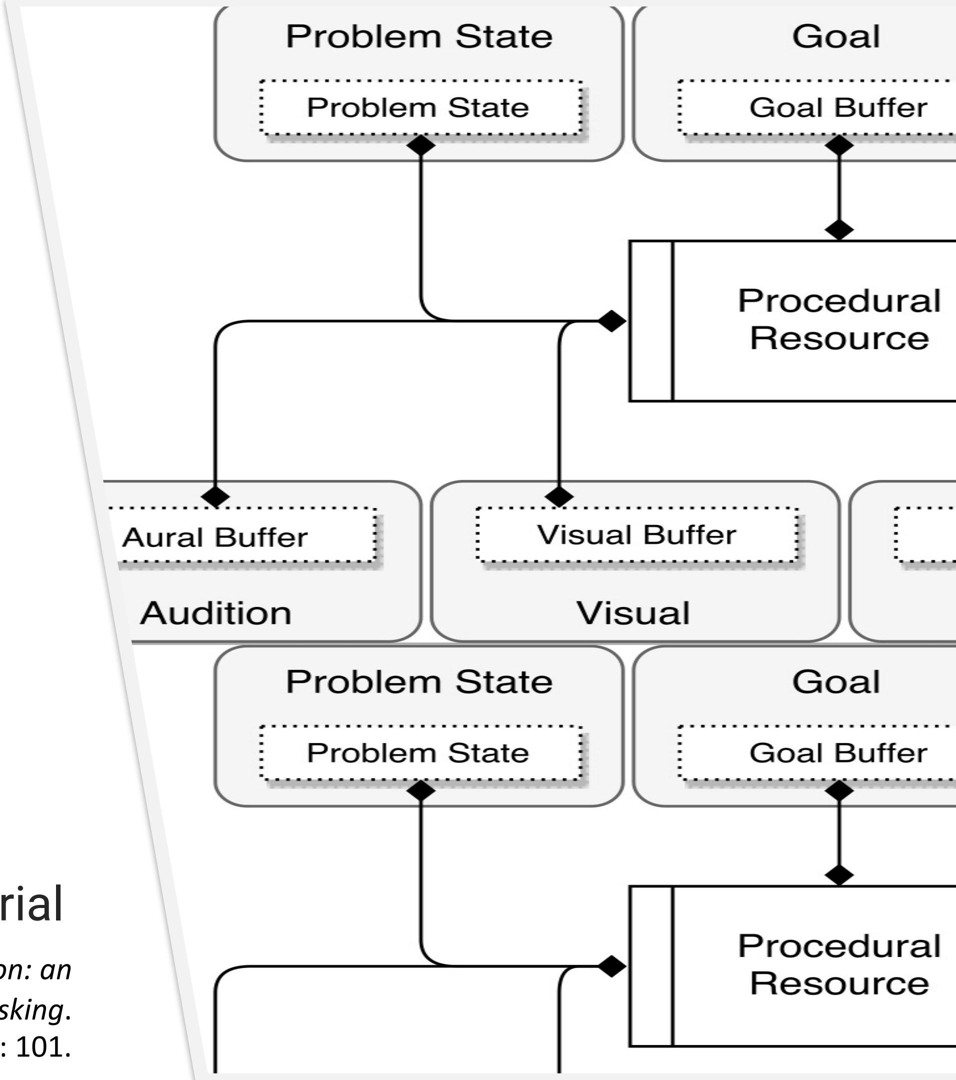
Also confirmed:

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

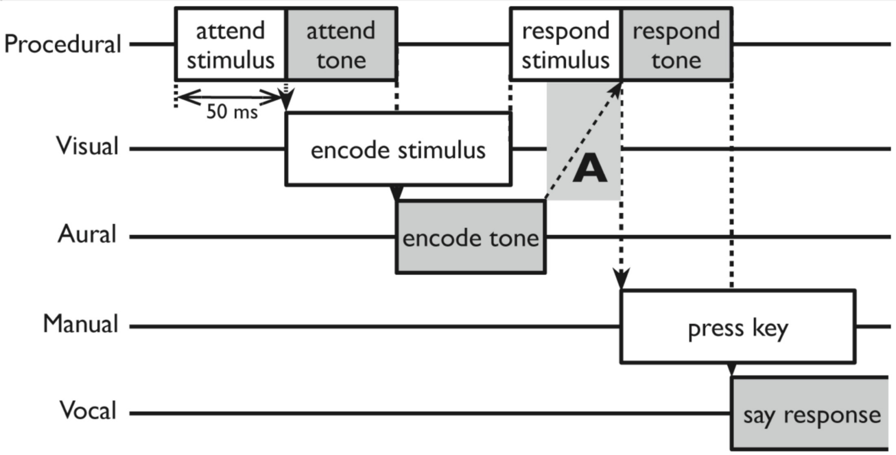


Salvucci and Taatgen. *Threaded cognition: an integrated theory of concurrent multitasking*. Psychological review 115.1 (2008): 101.

University of Ljubljana
Faculty of Computer and Information Science

Theory of Multitasking

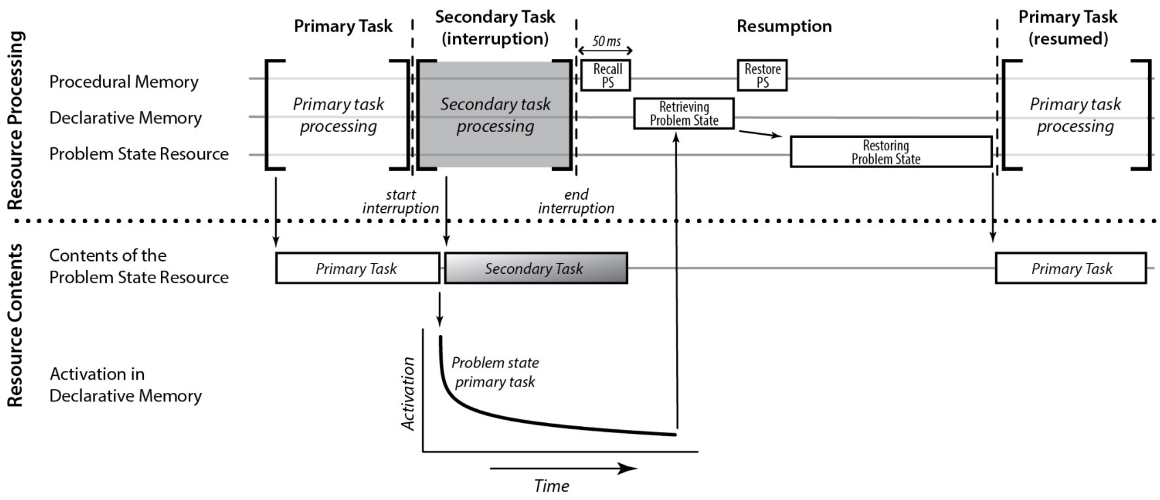
- Interference when two or more threads ask for the same resource at a time



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

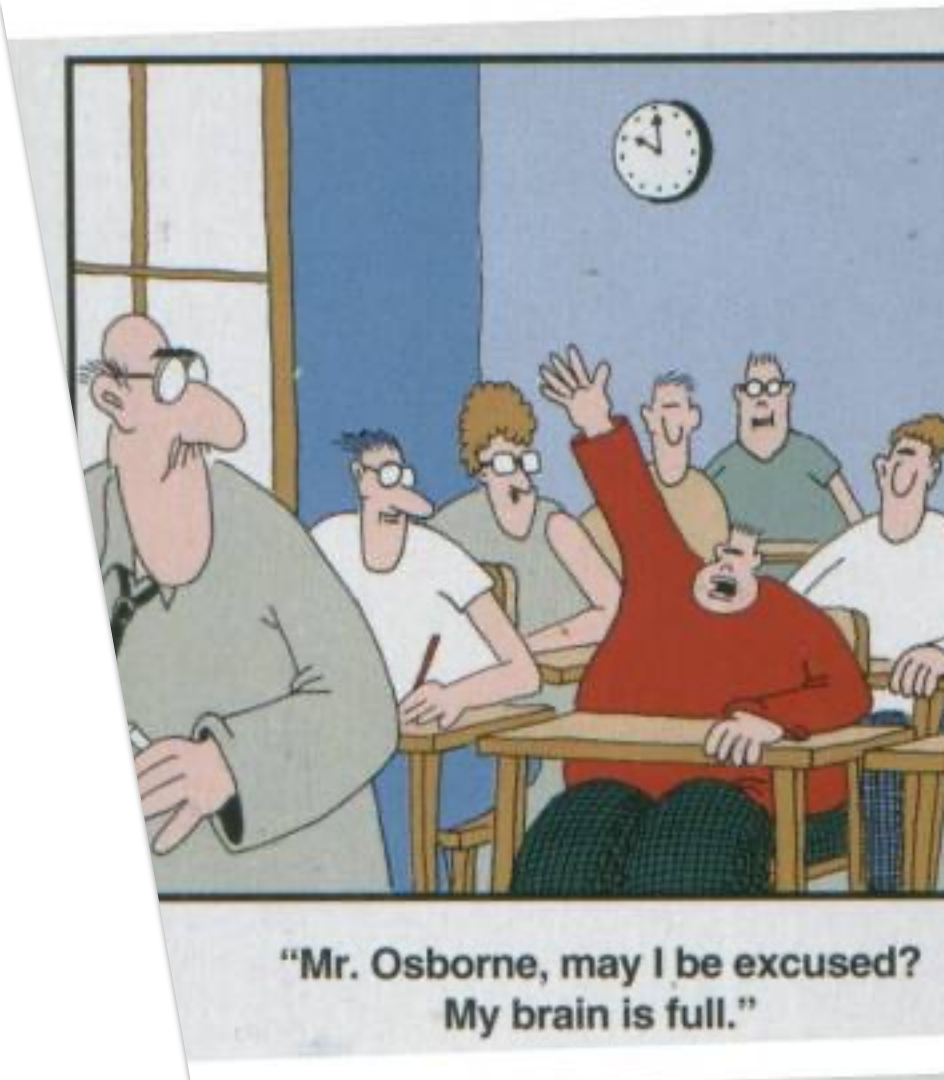
- Complex tasks require problem state saving/retrieving



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.

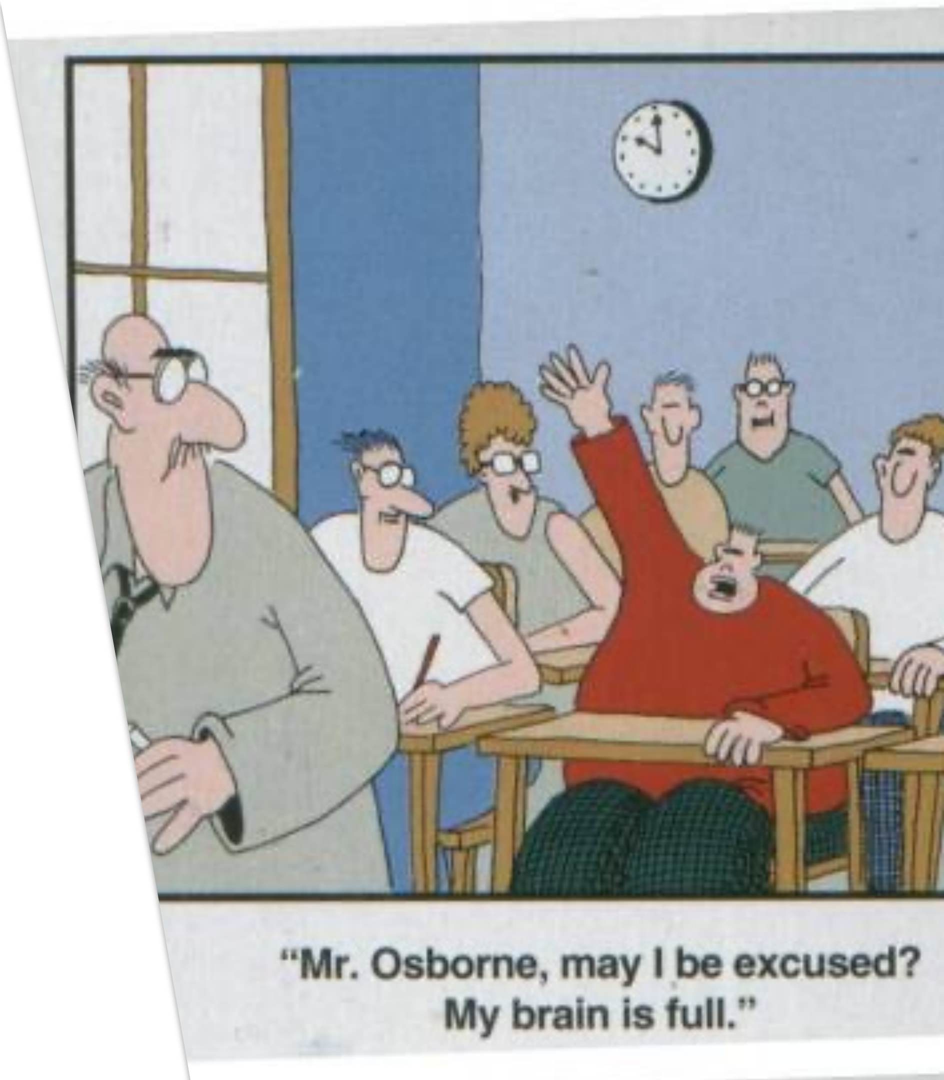
Implications on Mobile Attention Management

- Interruptions are more disruptive if they require problem state switching



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



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.

University of Ljubljana
Faculty of Computer and Information Science

No

University of Ljubljana
Faculty of Computer and Information Science

Can we automatically infer task engagement with wearables?

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.

University *of Ljubljana*
Faculty *of Computer and Information Science*

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

University *of Ljubljana*
Faculty *of Computer and Information Science*

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

- 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 performance)
  - 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

Cognitive Load Prediction

- Cast into a 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%	

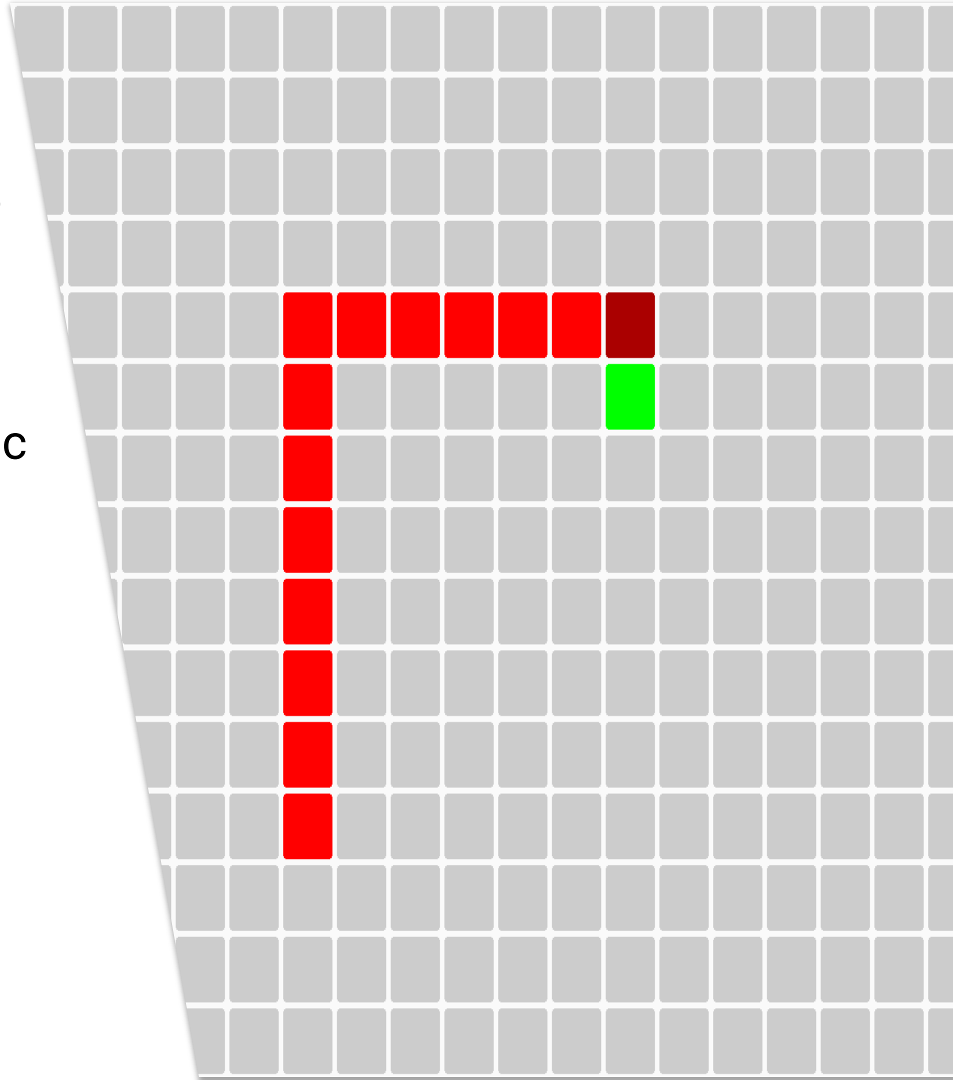
What if the task is a mobile game?

T. Knez, M. Gjoreski, and V. Pejović,
Analiza vpliva težavnosti računalniške igre na izmerjenevrednosti fizioloških signalov
HCI-IS ’19, Ljubljana, Slovenia

Collected Data

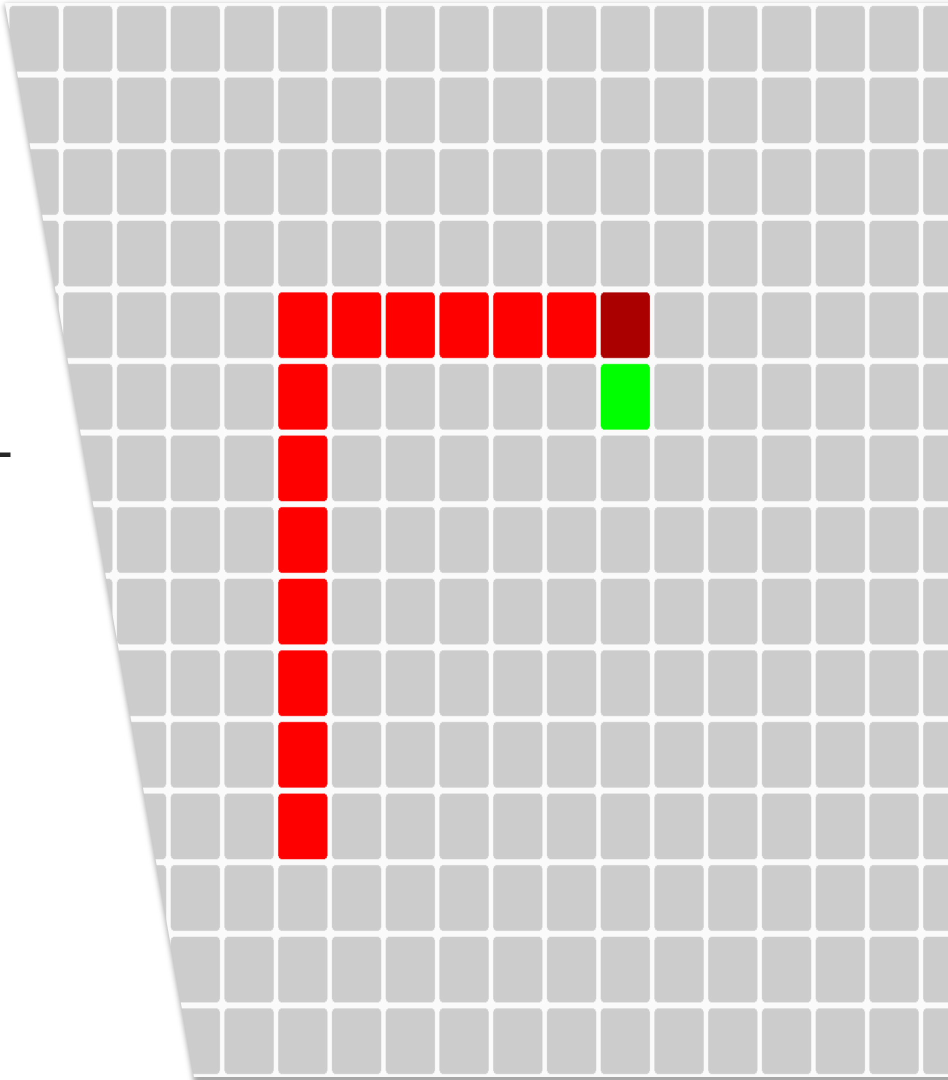
https://gitlab.fri.uni-lj.si/lrk/mobile-cogload-dataset

- Physiological signals with MS Band 2
  - Heart rate intervals (R-R), galvanic skin response (GSR) and skin temperature (ST)
- Mobile game
  - Objective difficulty data
  - Subjective difficulty (NASA-TLX)
- Personality test



Cognitive Load Prediction

- Predicting subjective difficulty was not achieved
- Objective difficulty for the two-class problem (easy vs difficult) predicted with 67% accuracy (c.f. 59% baseline)
- Heart rate and skin conductance features are the most informative



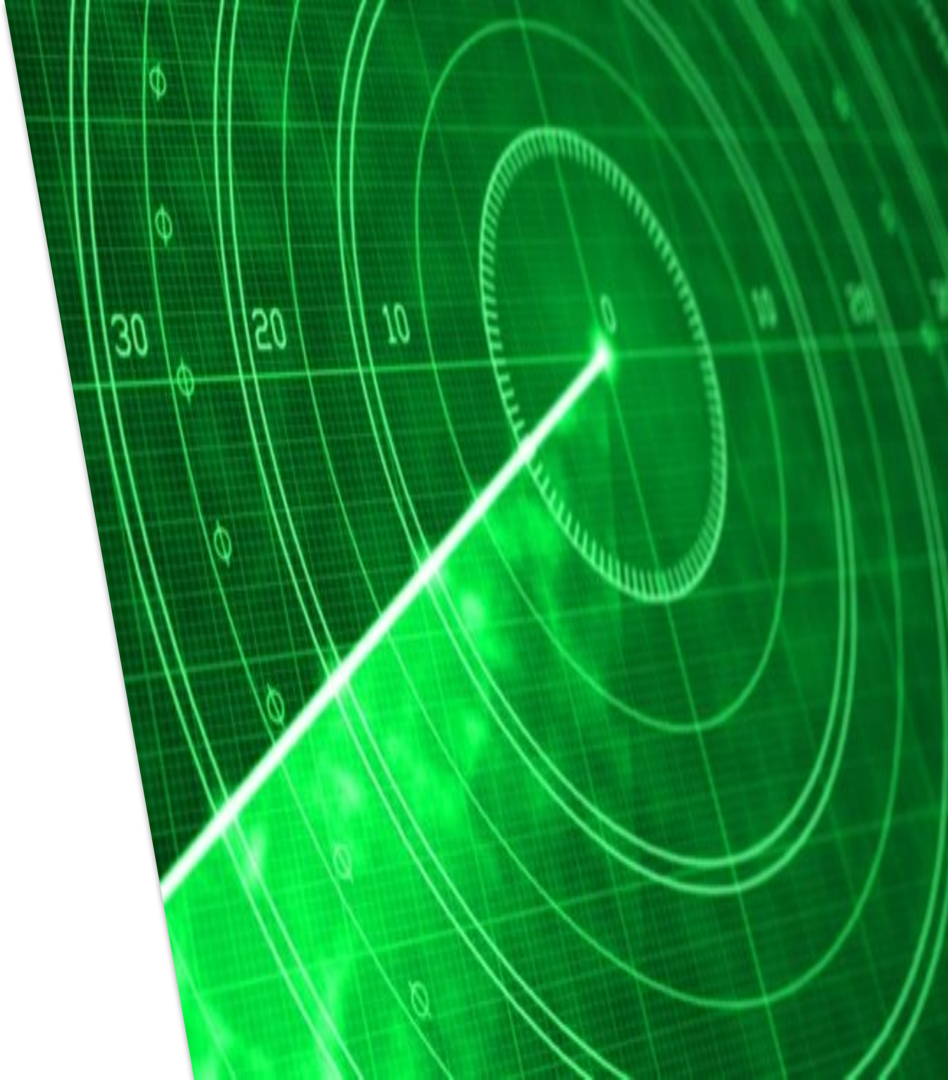
Fully unobtrusive task engagement inference

University of Ljubljana
Faculty of Computer and Information Science

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

Wireless Cognitive Load Inference

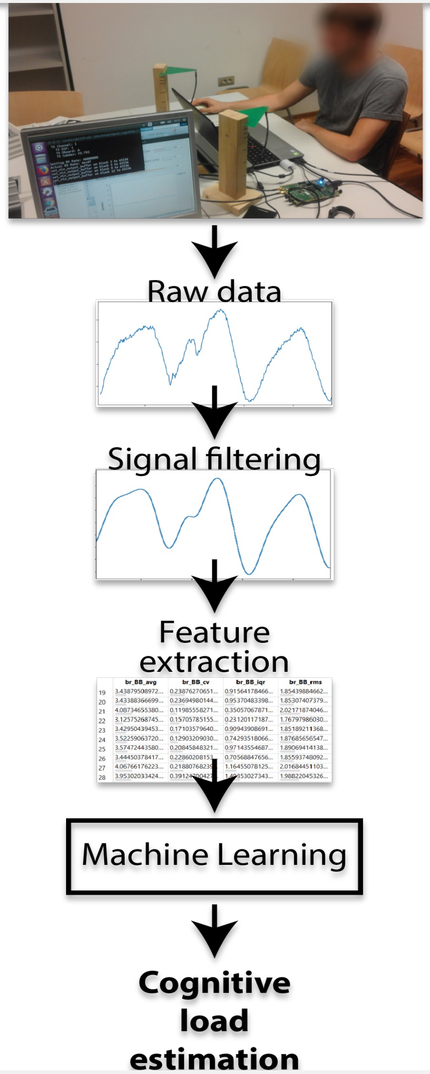
- **Premise:** radar can detect breathing and heart beat related body movement
- **Path:** custom radar
- **Hypothesis:** filtered radar signals as a basis for ML models of CL



University *of Ljubljana*
Faculty *of Computer and*
Information Science

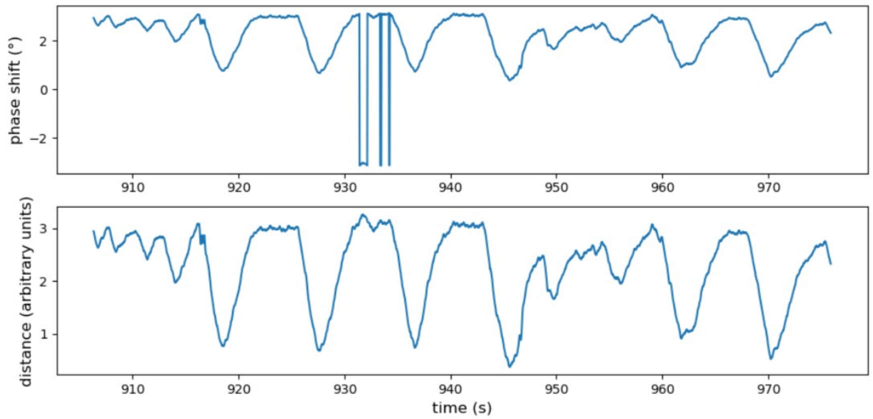
Wi-Mind

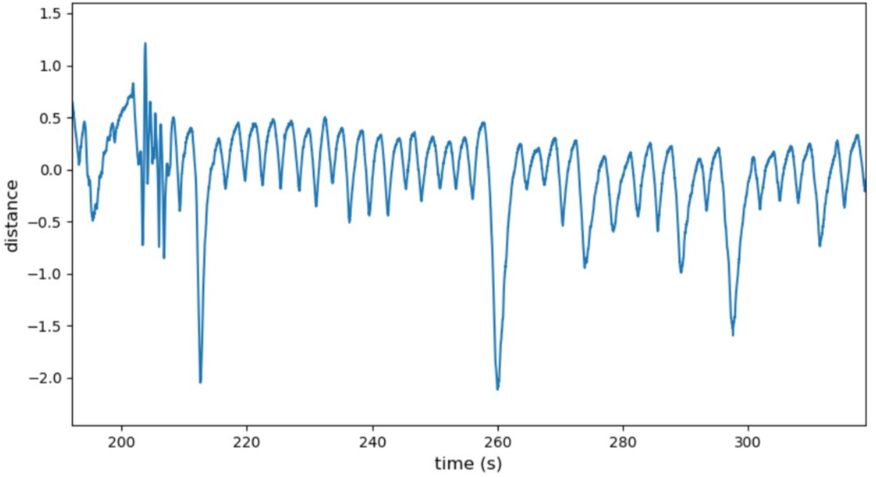
- Software-Defined Radio (SDR) implementation of FMCW radar followed by phase analysis
- Monitor movement as a user is solving tasks of different difficulty
- Extract heart beat and breathing-related features
- Build ML models



From EM Waves to Physiological Signals

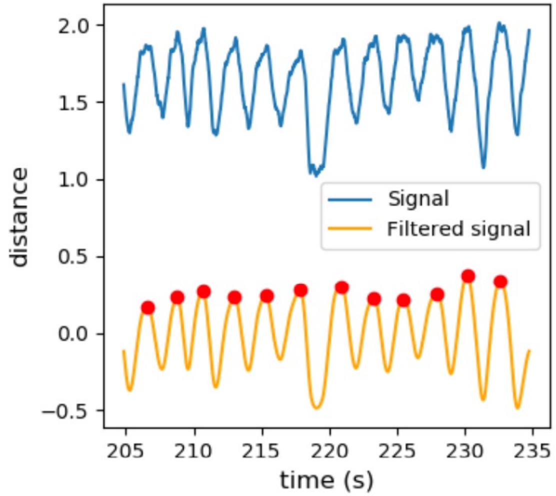
- Preprocessing:
  - Unwrapping phase
  - Filtering HF and LF noise

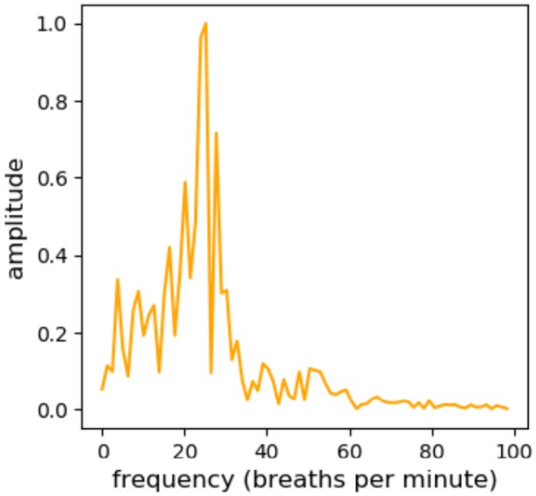




From EM Waves to Physiological Signals

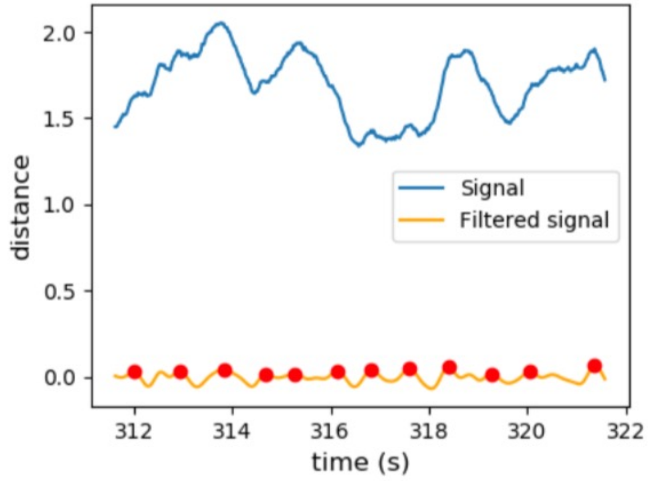
- Preprocessing:
  - Unwrapping phase
  - Filtering HF and LF noise
- Extracting breathing signal
  - Breathing rate (via FFT) features: mean rate, power in different bands, etc.
  - Inter-breath features (peak detection): avg. interval, variation, I:E, etc.
- Meta-feature
  - Is the signal “clean”?

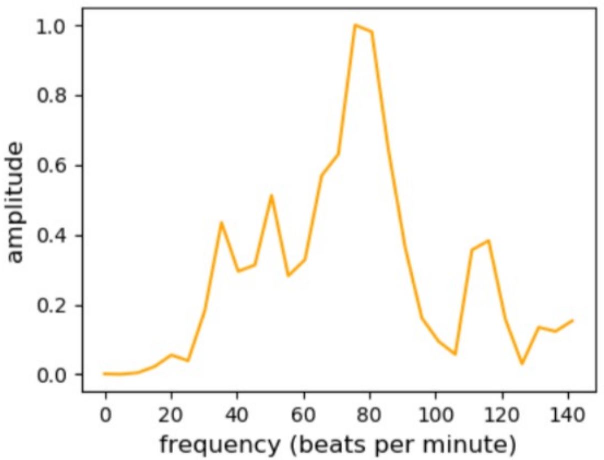




From EM Waves to Physiological Signals

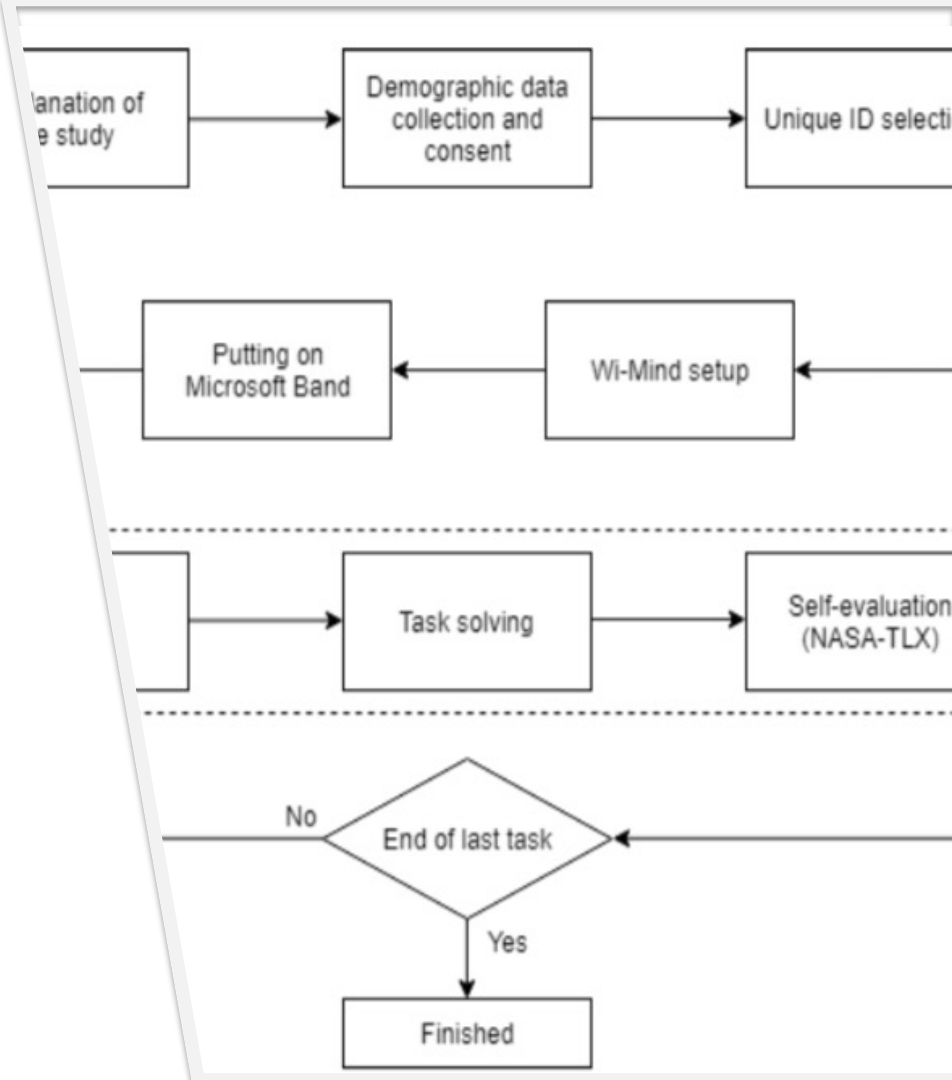
- Preprocessing:
  - Unwrapping phase
  - Filtering HF and LF noise
- Extracting heart beat signals:
  - Heart rate (FFT)
  - Heart rate variability HRV (peak detection + filtering) features: RR intervals, LF and HF HRV





WiMind Experiments

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



University of Ljubljana
Faculty of Computer and Information Science

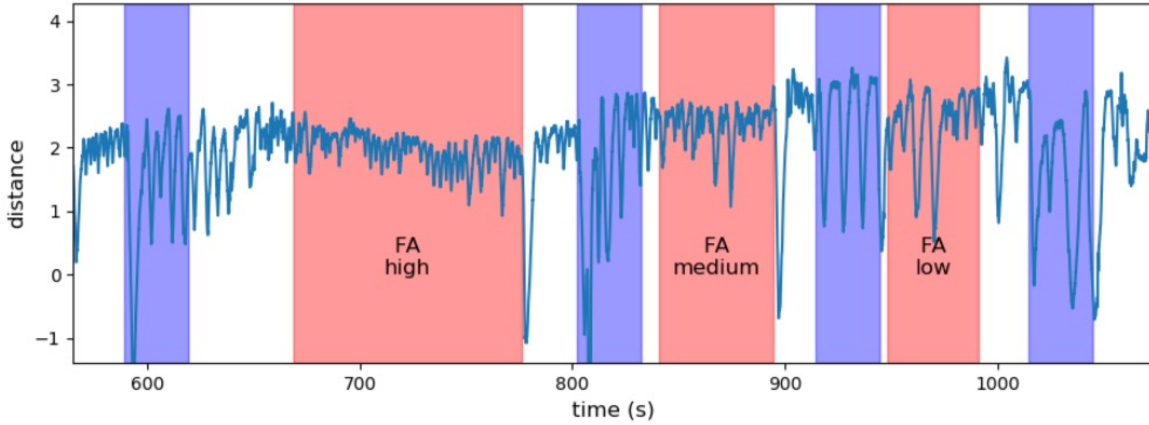
WiMind Experiments

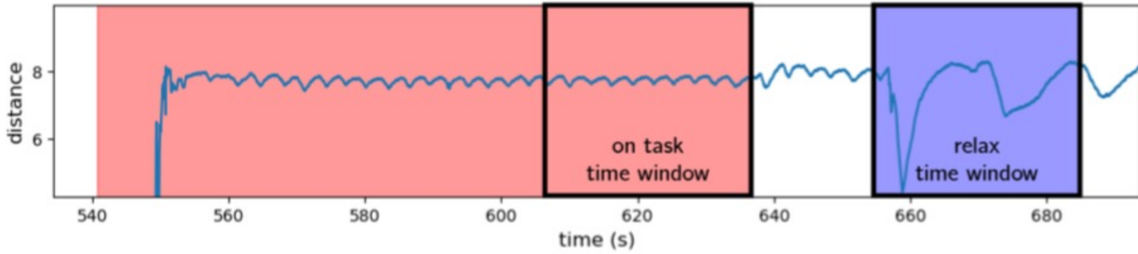
- Primary (PC-based) task
  - Adapted from Haapalainen et al.
  - NASA TLX after each task
- WiMind wireless measurements
- MS Band + Android app
- Demographics
  - 23 users
  - 20-38 years old
  - 6 female, 17 male

University of Ljubljana
Faculty of Computer and Information Science

Results

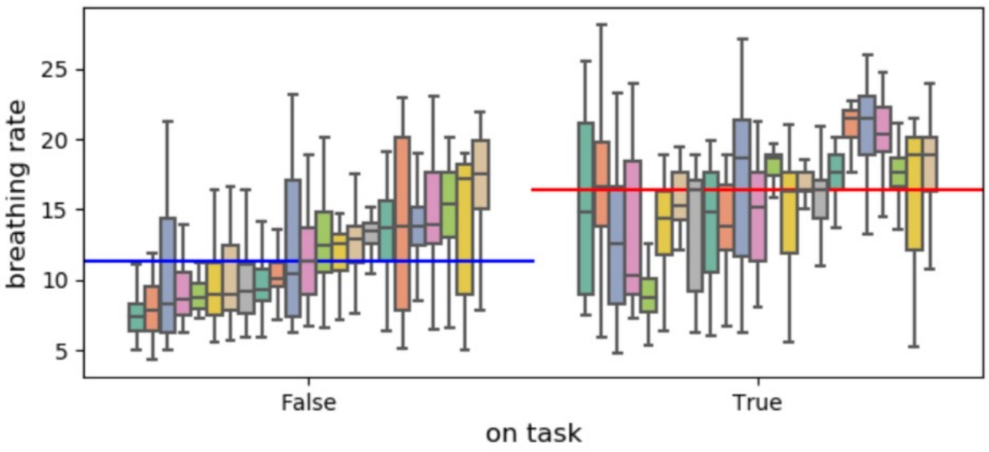
- Labelling signals via time windows:
  - Last 30 seconds of task engagement (label “busy”)
  - 30 seconds of explicit relaxation (label “relax”)



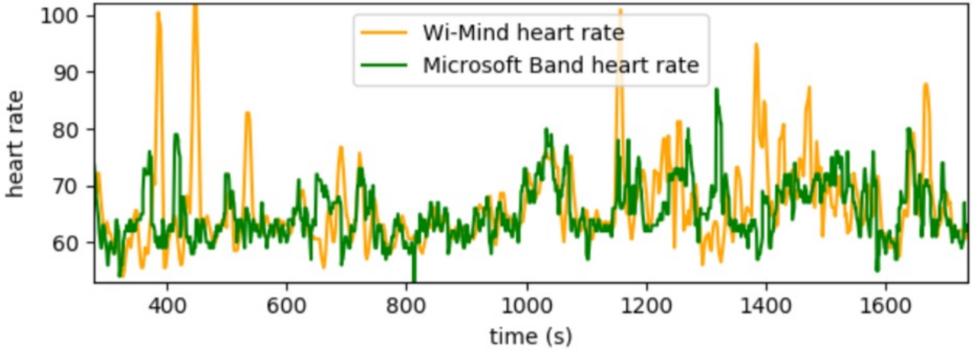


But first…

- Breathing rate validation



- Heart rate validation



University of Ljubljana
Faculty of Computer and Information Science

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

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

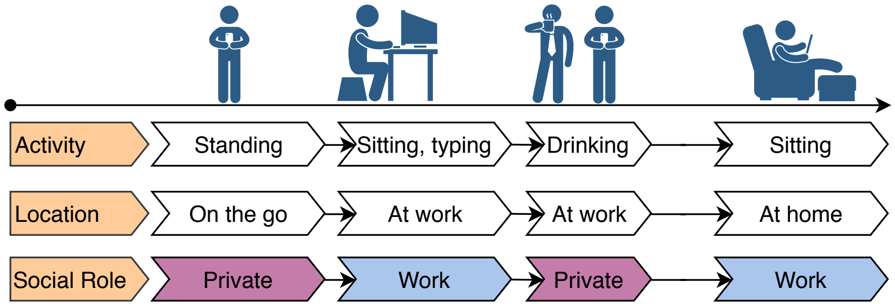
University of Ljubljana
Faculty of Computer and Information Science

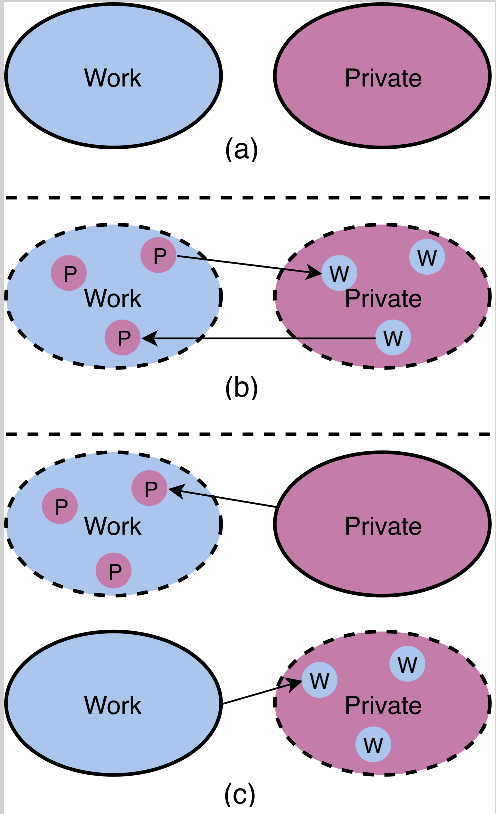
Research Directions

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

Research Directions

- How do social roles impact interruptibility?





University of Ljubljana
Faculty of Computer and Information Science

C.Anderson, et al.
The Impact of Private and Work-Related Smartphone Usage on Interruptibility
Ubittention workshop with ACM UbiComp'19, London, UK

Collaboration Opportunities

- Pick up our work and develop it further:
  - InterruptMe on Bitbucket
  - Wi-Mind on Github (data, too)
  - Wearables study data on Github
  - “A Survey of Attention Management Systems in Ubiquitous Computing Environments” by Anderson et al., ACM IMWUT (Ubicomp) 2018

University *of Ljubljana*
Faculty *of Computer and Information Science*

Collaborators

- Wi-Mind:
  - Tilen Matkovič, Uni. of Ljubljana
- Wearables:
  - Martin Gjoreski, Mitja Luštrek, Institut Jožef Stefan, Ljubljana
  - Timotej Knez, Uni. of Ljubljana
- TaskyApp:
  - Gašper Urh, Uni. of Ljubljana
- Mobile Interruptibility:
  - Christoph Anderson, University of Kassel
  - Abhinav Mehrotra, Samsung AI, UK
  - Mirco Musolesi, University College London

University *of Ljubljana*
Faculty *of Computer and Information Science*

Thank You!

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


Credit: Shutterstock.com

Dr Veljko Pejović

Faculty of Computer and Information Science

University of Ljubljana, Slovenia

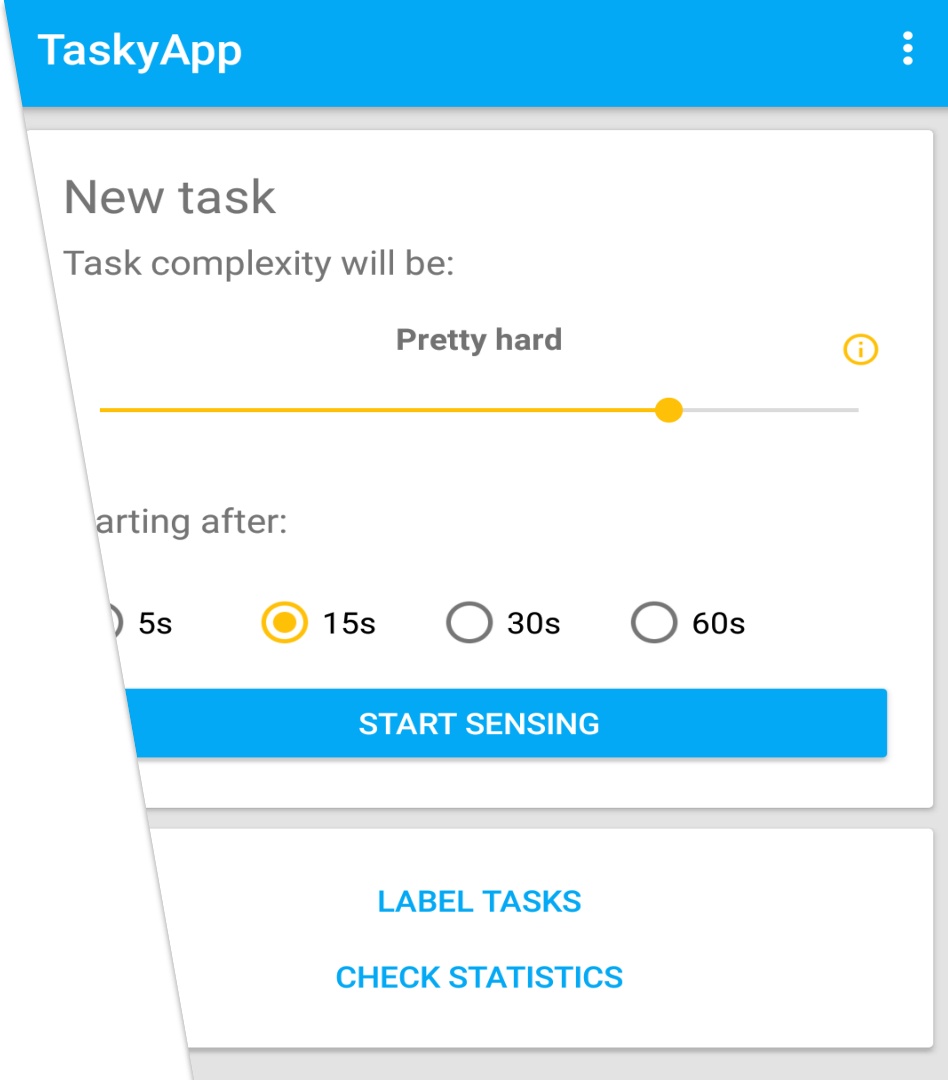
Veljko.Pejovic@fri.uni-lj.si

@veljkoveljko

University *of Ljubljana*
Faculty *of Computer and Information Science*

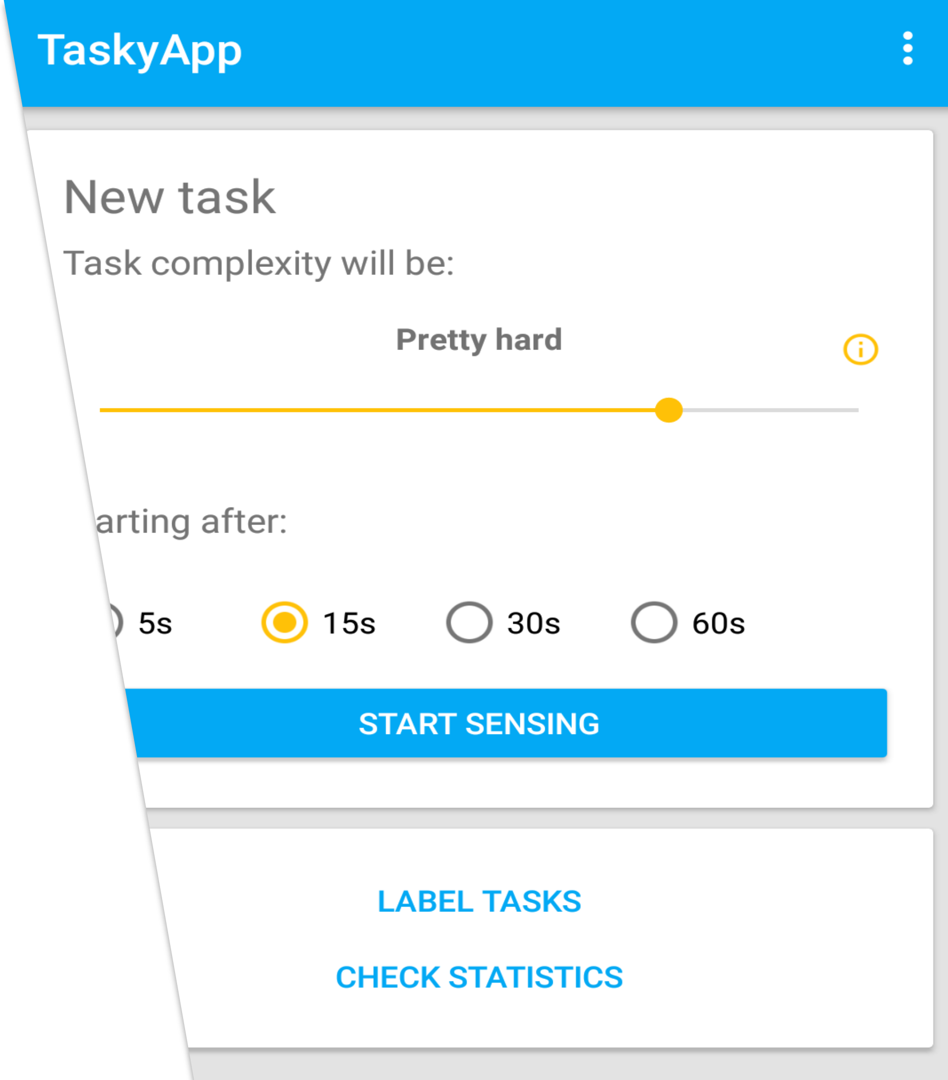
TaskyApp

- 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



University of Ljubljana
Faculty of Computer and Information Science

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

What’s the role of social roles?

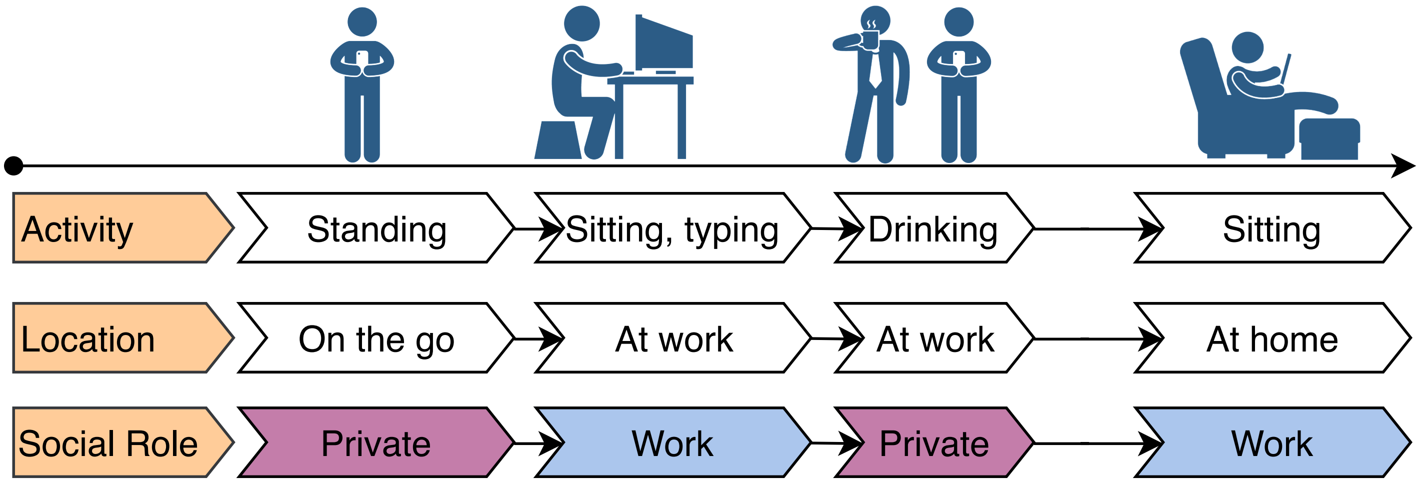
University of Ljubljana
Faculty of Computer and
Information Science

Social Role Theory

- People play roles
  - Work and family (private) are the most prominent roles
  - Our behaviour is driven by the assumed role

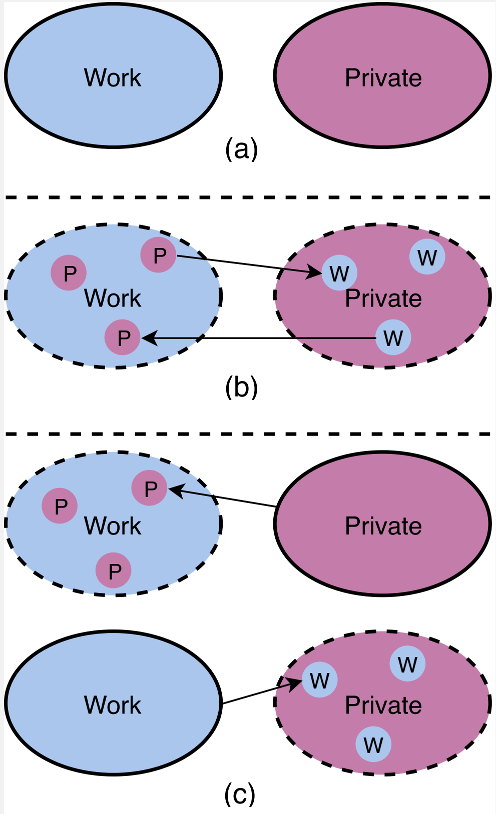
Social Role Theory

- Role is related to a wider context



Boundary Theory

- Role handling
  - Permeability of the role boundaries varies between roles and individuals
  - Personal preferences
    - Segmenters
    - Integrators
    - Private-first
    - Work-first



Impact of ICT

- Multiple roles may conflict
  - Time-based conflict
  - Strain-based conflict
  - Behaviour-based conflict
- ICTs can weaken the boundaries
- ICTs can also facilitate role switch
  - E.g. different email folders for private and work stuff

Research Questions

- How does the currently enacted role impact interruptibility?
- Do personal role boundary preferences modulate notification handling behaviour?
- Can we automatically detect the current role from smartphone usage data?

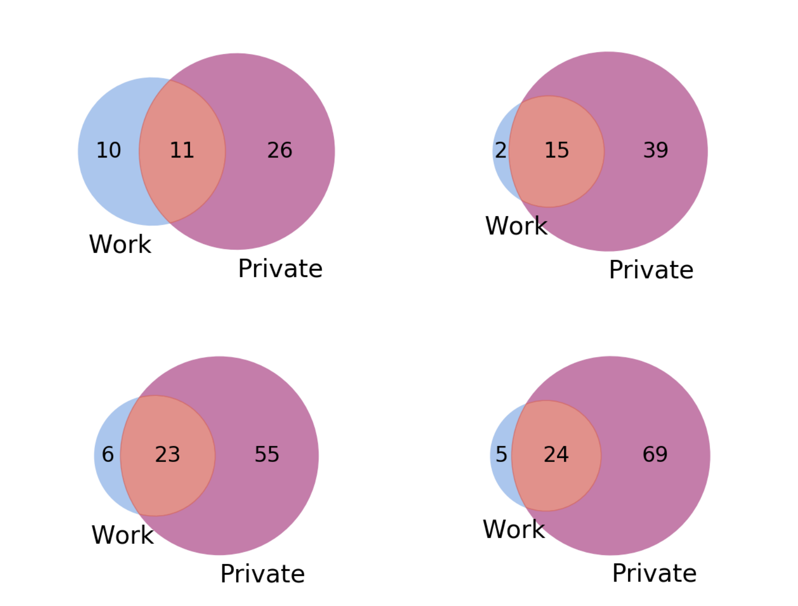
Methodology

- Android application
- Automated sensing
  - Notifications
  - Context
- Experience sampling
  - Social role
  - Interruptibility
- Four participants
- 11 weeks

University *of Ljubljana*
Faculty *of Computer and Information Science*

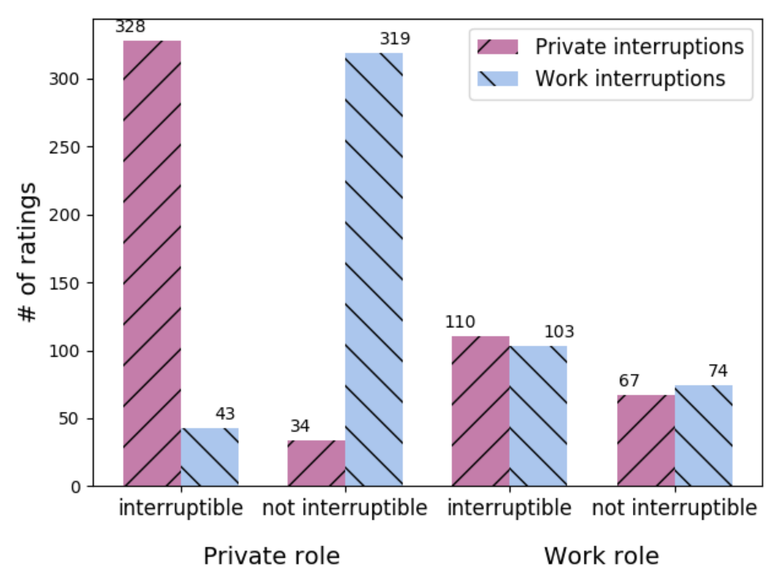
Roles and Smartphone Usage

- Application usage
  - Application sequence mining using Apriori algorithm
  - (User-)unique role-specific app sequences
  - Example:
    - {('Teams', 'System-UI', 'Gboard'}), ({'Teams', 'Gboard'}), ({'Einstellungen', 'System-UI'}), ({'Teams'}), ({'Slack'})...
    - ({'Chrome', 'Google News'}), ({'Chrome', 'Gboard'}), ({'WhatsApp', 'Delta'}), ({'System-UI', 'Google News'}), ({'Chrome', 'Delta'}), ({'Delta', 'Gboard'})...



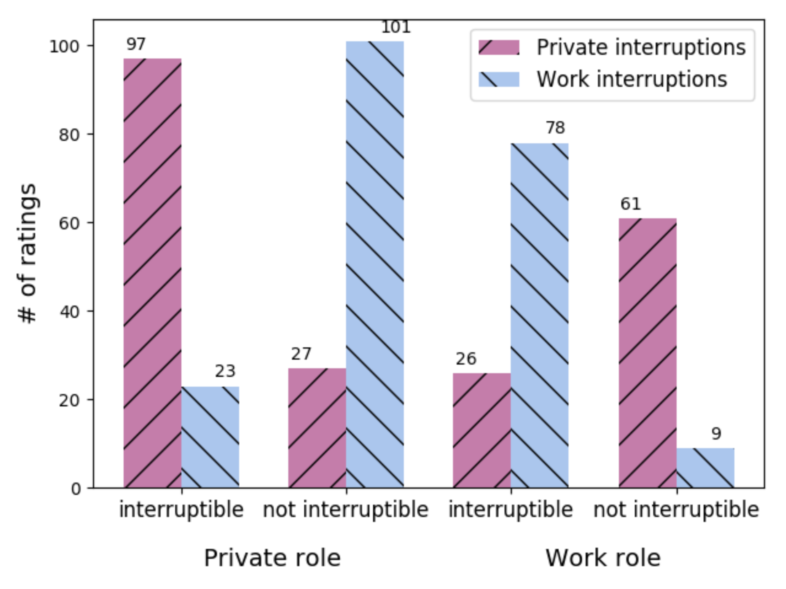
Roles and Interruptibility

- Both current role and individual preferences impact notification handling
  - User #1:
    - Slightly more interruptible at work
    - Firm work->private boundary
    - More permeable private->work
    - Private-first person



Roles and Interruptibility

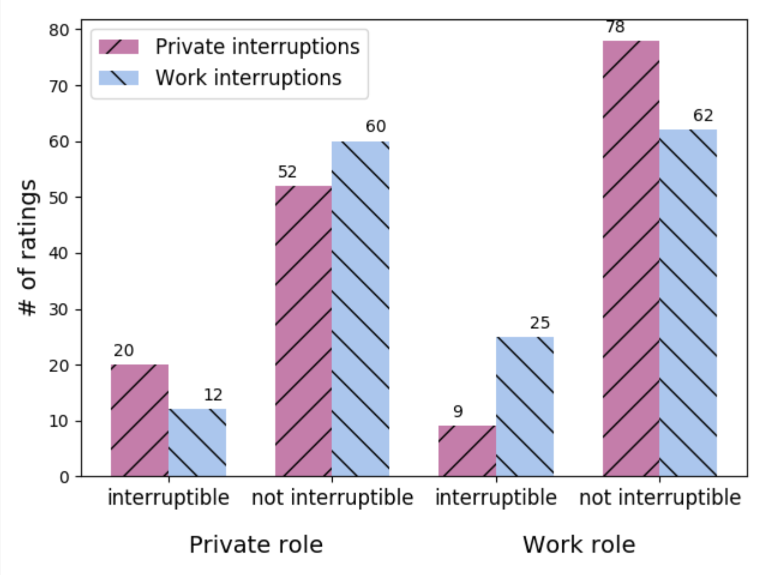
- Both current role and individual preferences impact notification handling
  - User #2:
    - Slightly more interruptible at work
    - Firm work->private boundary
    - Firm private->work
    - Segmenter



University of Ljubljana
Faculty of Computer and Information Science

Roles and Interruptibility

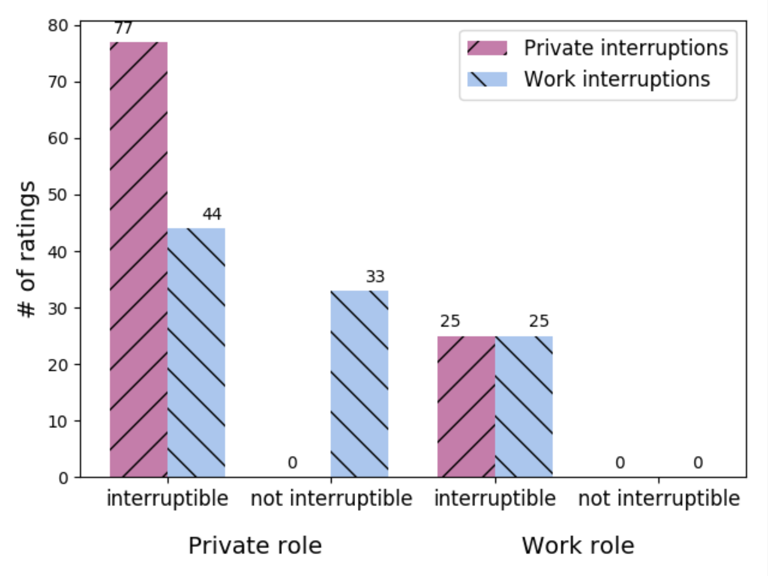
- Both current role and individual preferences impact notification handling
  - User #3:
    - Lower interruptibility throughout
    - Loose work->private boundary
    - Loose private->work boundary
    - Integrator (to an extent)



University of Ljubljana
Faculty of Computer and Information Science

Roles and Interruptibility

- Both current role and individual preferences impact notification handling
  - User #4:
    - High interruptibility throughout
    - Loose private->work boundary
    - Firmer work->private boundary
    - Private-first (to an extent)

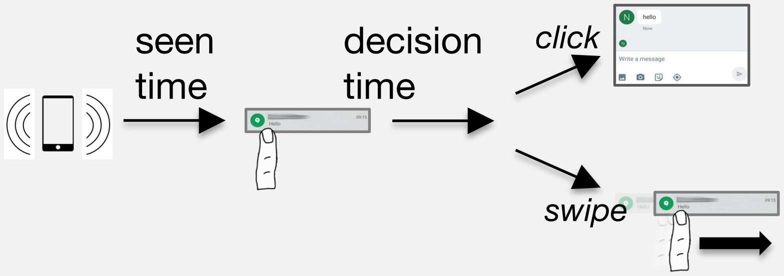


Why Does this Matter?

- "Influence of smartphone on workplace stress is modulated by how individuals use smartphones and how they desire to use them"
  Stich et al., *Workplace stress from actual and desired computer-mediated communication use: a multi-method study*, 2017
- We investigated disruptiveness of mobile notifications
  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.

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



University *of Ljubljana*
Faculty *of Computer and*
Information Science

Disruptiveness: Impact of Sender

- Most disruptive notifications come from:
  - Subordinates at work
  - Colleagues
- Least disruptive:
  - Family

However, no info on the current social role in this dataset

University of Ljubljana
Faculty of Computer and Information Science

Next Steps

- Learn how people want to use ICTs
- Observe how people actually use ICTs
- Adapt notification management to user cater to needs

Next Steps

- Large-scale multi-device study
  - PC and phone usage monitoring
  - ESM
- Infer social roles from apps
- Infer preferences from phone usage
  - Silent mode activated
  - Notification dismissed
- Tuneable notification management system