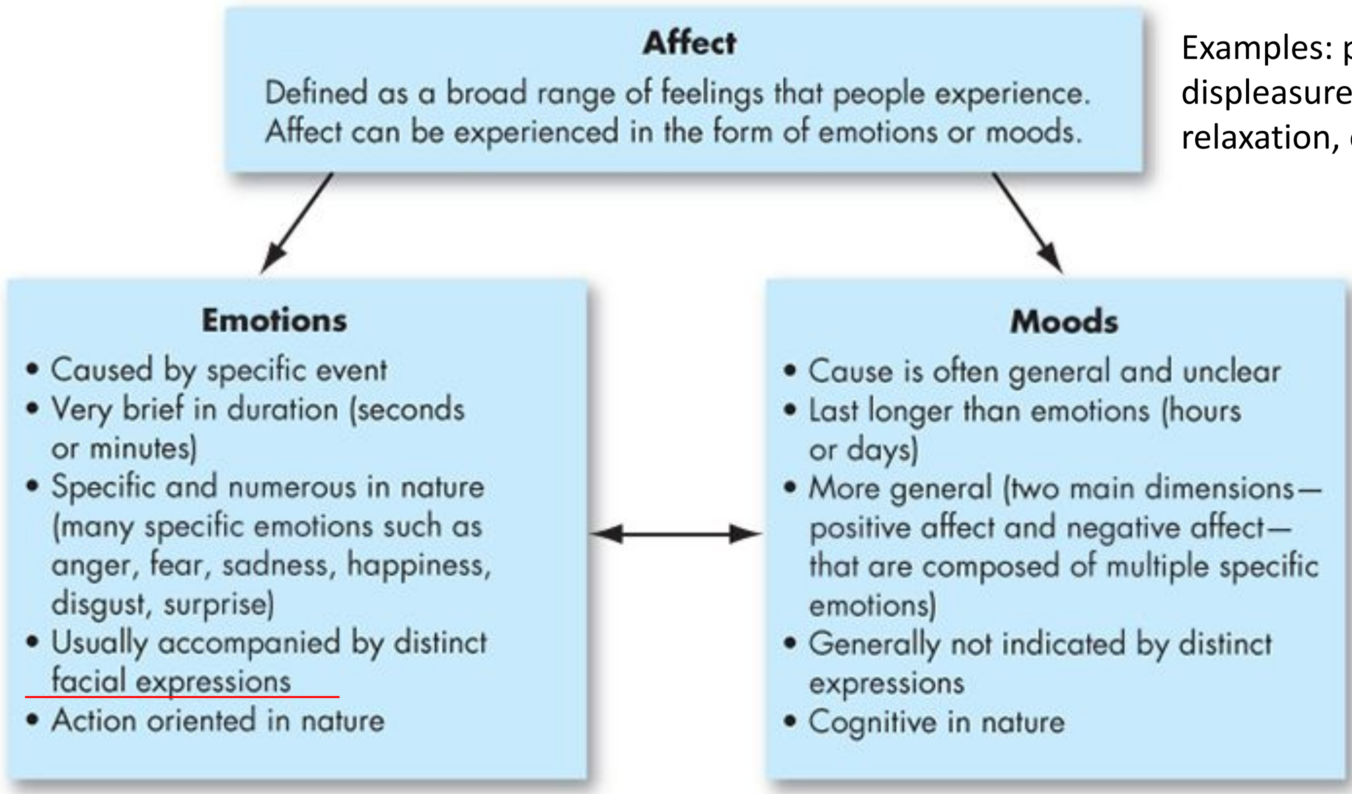
Sensor Data Applications: Mental Health (Emotion)

Affect, emotion, and mood



Examples: pleasure and displeasure, tension and relaxation, energy and tiredness

Essentials of Organizational Behavior, 14/e by Stephen P Robbins, Timothy A. Judge
https://www.oreilly.com/library/view/essentials-of-organizational/9780134523859/xhtml/fileP7001012230000000000000000000C43.xhtml
Affect, Mood, and Emotion Differences, 2012 Ekkekakis, PhD
https://web.archive.org/web/20160313201333/http://www.public.iastate.edu/~ekkekaki/pdfs/ekkekakis_2012.pdf

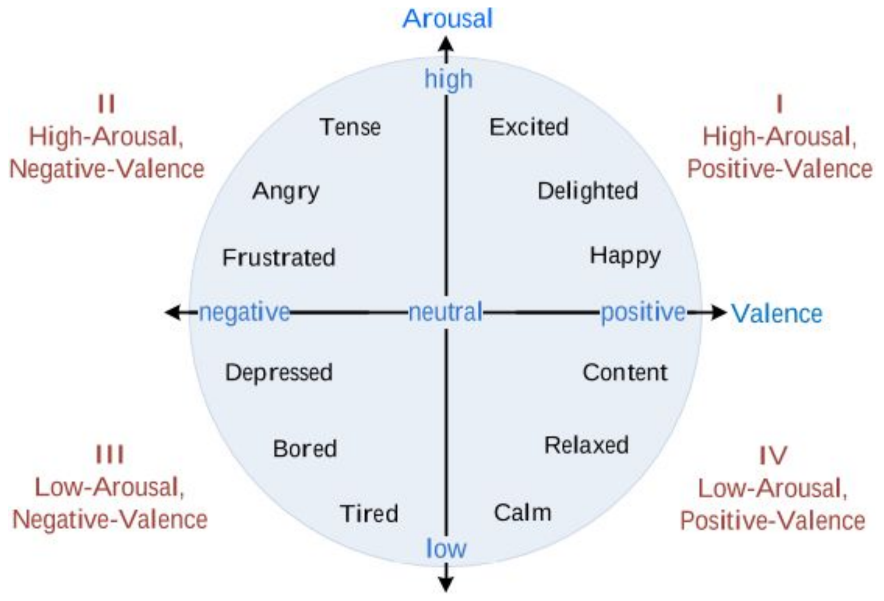
Emotion duration

- Emotions start with occurrence of an external or internal event
- Emotions are generally not flash-like responses but typically last for several minutes, hours, or even longer (Frijda et al., 1991)
- Moods are often also differentiated from emotions based on a duration criterion with emotions being considered as shorter than moods (Beedie, Terry, & Lane, 2005).
- This relative order does, however, not imply that emotions are in absolute terms always or even typically short (Frijda et al., 1991).

Determinants of Emotion Duration and Underlying Psychological and Neural Mechanisms
Philippe Verduyn, Pauline Delaveau, Jean-Yves Rotgé, 2015
https://doi.org/10.1177%2F1754073915590618

Psychometric Models

- Finding a representative set of **<u>affect adjectives</u>** via statistical analysis (e.g., factor analysis)
- James Russell's Affect Circumplex: Valence vs. Arousal



- A circumplex is a circular arrangement of objects such that the angular distance between them represents the correlation between them
- That is, objects that are close together on the circumplex are very similar to each other, or very likely to co-occur

Seemo: A Computational Approach to See Emotions, CHI 2018

Basic emotion

- Universal basic emotions (Ekman, 1992)
  - Mostly used for emotion reading from facial expression

Paul Ekman. 1992. An argument for basic emotions. Cognition & emotion, 6, 3-4 (1992), 169-200.
https://blog.affectiva.com/the-emotion-behind-facial-expressions

Measuring Emotion

- Stimulus (reaction) approaches
  - Eliciting specific emotional states via a given stimulus (that's why it's also known as stress elicitation)
  - Ground truth labeling strategies:
    - **Stimulus' label** is considered as ground truth
    - OR, **a user's self-report** about their emotional state can be considered as ground truth
- Experience sampling approaches
  - Self-reporting a user's feeling via experience sampling (or in-situ self-report about current mood)
  - Unlike "emotion", it's not event targeted; and thus, it is more or like a user's current mood

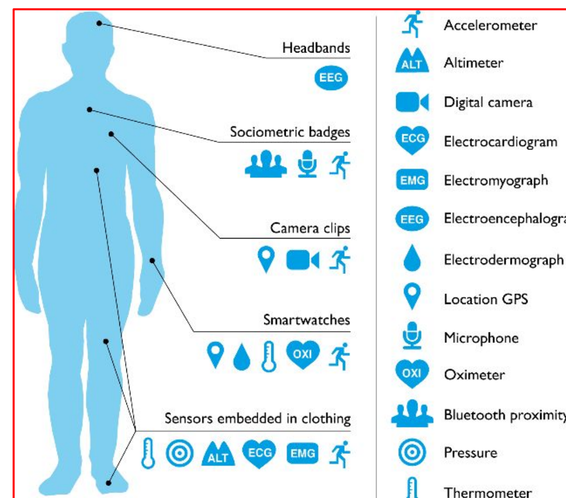
Stimulus

Picture, Movie, or Song

Self-report

Dimension	Question: To what extent does this make you feel (1. . . 9)
Approach	Like this is something you would want to approach? (desire to avoid. . . desire to approach)
Arousal	Stimulated? (more subdued. . . more stimulated)
Attention	Focused? (more unfocused. . . more focused)
Certainty	Certain? (very uncertain. . . very certain)
Commitment	A sense of commitment to an individual or creature? (lack of commitment to an individual/ creature . . . strong commitment to an individual/creature)
Control	Like things are under control? (things seem out of control. . . things seem under control)
Dominance	Dominant? (more submissive. . . more dominant)
Effort	Like viewing this demands effort? (no effort whatsoever. . . enormous effort)
Fairness	Like things are fair? (sense of unfairness. . . sense of fairness)
Identity	Like you identify with a group of people? (lack of group identity. . . strong group identity)
Obstruction	Like you're obstructed by something? (very unobstructed. . . very obstructed)
Safety	A sense of safety? (very unsafe. . . very safe)
Upswing	Like this went better than it first seemed it would? (worse than expected. . . better than expected)
Valence	Pleasant? (very unpleasant. . . very pleasant)

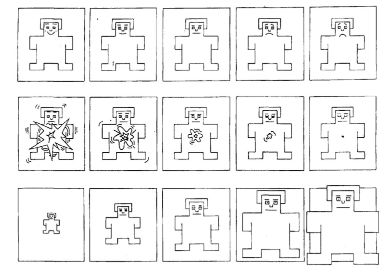
Sensor Data Collection

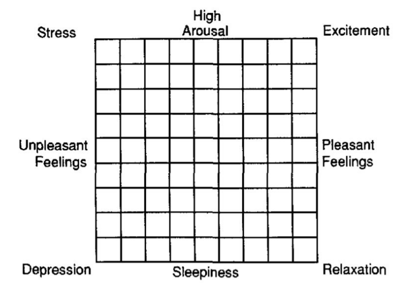


Self-reporting measures assessing affect, mood, and emotion

Single-Item Dimensional Measure of Affect

Construct	Measure	Dimension	Source
Core affect	Self-Assessment Manikin (SAM)	Valence (pleasant to unpleasant), arousal (excited to calm), dominance (feeling of being controlled versus being in control)	Lang (1980); Bradley & Lang (1994)
Core affect	Affect Grid (AG)	Pleasure and arousal	Russell, Weiss, & Mendelsohn (1989)
Affective valence (pleasure and displeasure)	Feeling Scale (FS)	Affective valence (pleasure and displeasure)	Hardy & Rejeski (1989)
Felt arousal	Felt Arousal Scale (FAS)	Felt arousal	Svebak & Murgatroyd (1985)



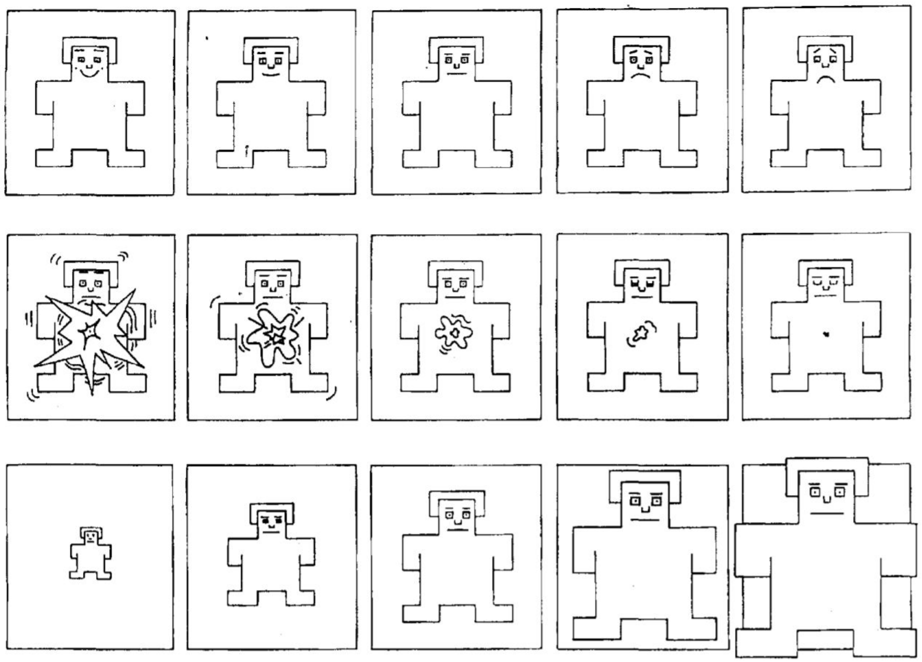


11-point bi-polar scale:
-5 = "Very bad“
0="Neutral"
+5 = "Very good"

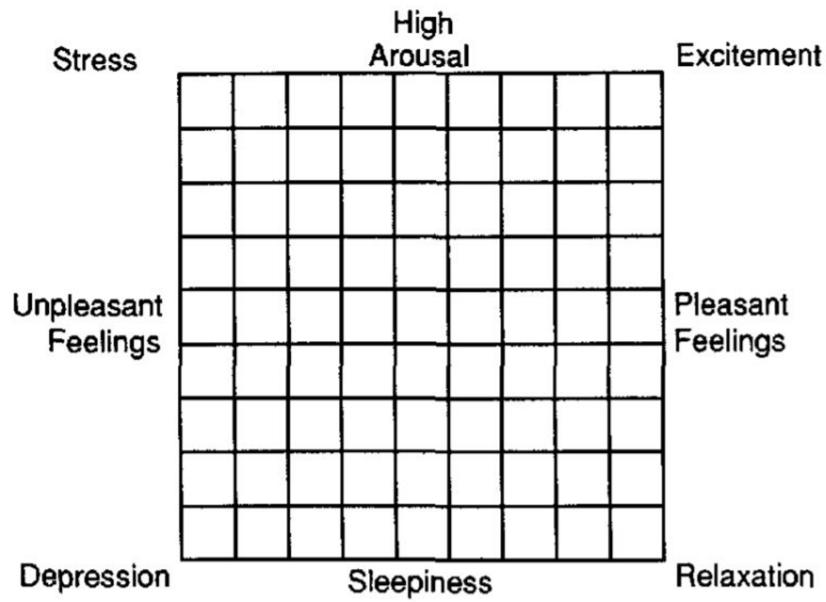
6-point scale:
1 = "Low arousal"
6 = "High arousal"

Affect, Mood, and Emotion Differences, 2012 Ekkekakis, PhD
https://web.archive.org/web/20160313201333/http://www.public.iastate.edu/~ekkekaki/pdfs/ekkekakis_2012.pdf

Self-reporting measures assessing affect, mood, and emotion



SAM



Affect Grid

SAM: Measuring emotion: The self-assessment manikin and the semantic differential, 1994
http://www.cnbc.pt/jpmatos/29.%20Bradley.pdf
Affect Grid (Russel & Weiss, 1989)
https://www.researchgate.net/publication/232501584_Affect_Grid_A_Single-Item_Scale_of_Pleasure_and_Arousal

Multi-Item Measures of Distinct Mood States

Construct	Measure	Dimension	Source
Multiple distinct affective states	Revised Multiple Affect Adjective Checklist (MAACL-R)	Anxiety (A), depression (D), hostility (H), positive affect (PA), and sensation seeking (SS) *or* dysphoria (DYS; A + D + H) and PASS (PA + SS)	Zuckerman & Lubin (1985)
Multiple distinct mood states	Profile of Mood States (POMS)	Tension and anxiety, anger and hostility, fatigue and inertia, depression and dejection, vigor and activity, confusion and bewilderment	McNair, Lorr, & Droppleman (1971)
Mood dimensions	Positive and Negative Affect Schedule (PANAS)	Positive affect and negative affect	Watson, Clark, & Tellegen (1988)
Mood dimensions	Activation Deactivation Adjective Checklist (AD ACL)	Energy, tiredness, tension, and calmness *or* energetic arousal and tense arousal	Thayer (1989)
Mood dimensions	Four-Dimension Mood Scale (4DMS), state version	Positive energy, tiredness, negative arousal, and relaxation	Gregg & Shepherd (2009)

PANAS

Positive affect	Negative affect
Attentive	Hostile
Active	Irritable
Alert	Ashamed
Excited	Guilty
Enthusiastic	Distressed
Determined	Upset
Inspired	Scared
Proud	Afraid
Interested	Jittery
Strong	Nervous

Affect, Mood, and Emotion Differences, 2012 Ekkekakis, PhD
https://web.archive.org/web/20160313201333/http://www.public.iastate.edu/~ekkekaki/pdfs/ekkekakis_2012.pdf

Self-reporting measures assessing affect, mood, and emotion

- **Positive and Negative Affect Scales (PANAS)** scale (Watson and Tellegen, 1988)
  - Multiple items for each affect (positive vs. negative affect)

Positive affect	Negative affect
Attentive	Hostile
Active	Irritable
Alert	Ashamed
Excited	Guilty
Enthusiastic	Distressed
Determined	Upset
Inspired	Scared
Proud	Afraid
Interested	Jittery
Strong	Nervous

1	2	3	4	5
Very Slightly or Not at all	A Little	Moderately	Quite a Bit	Extremely

________ 1. Interested	________ 11. Irritable
________ 2. Distressed	________ 12. Alert
________ 3. Excited	________ 13. Ashamed
________ 4. Upset	________ 14. Inspired
________ 5. Strong	________ 15. Nervous
________ 6. Guilty	________ 16. Determined
________ 7. Scared	________ 17. Attentive
________ 8. Hostile	________ 18. Jittery
________ 9. Enthusiastic	________ 19. Active
________ 10. Proud	________ 20. Afraid

Development and validation of brief measures of positive and negative affect: the PANAS scales. Watson D, Clark LA, Tellegen A., 1988 https://www.ncbi.nlm.nih.gov/pubmed/3397865

Self-reporting measures assessing affect, mood, and emotion

- **Perceived Stress Scale (PSS)**
  - Multi items for accessing stress levels (e.g., 4, 10, or 14 items)

Perceived Stress Scale 4 (PSS-4)

INSTRUCTIONS
The questions in this scale ask you about your feelings and thoughts during THE LAST MONTH. In each case, please indicate your response by placing an "X" over the square representing HOW OFTEN you felt or thought a certain way.

	Never 0	Almost Never 1	Sometimes 2	Fairly Often 3	Very Often 4
1. In the last month, how often have you felt that you were unable to control the important things in your life?	☐	☐	☐	☐	☐
2. In the last month, how often have you felt confident about your ability to handle your personal problems?	☐	☐	☐	☐	☐
3. In the last month, how often have you felt that things were going your way?	☐	☐	☐	☐	☐
4. In the last month, how often have you felt difficulties were piling up so high that you could not overcome them?	☐	☐	☐	☐	☐

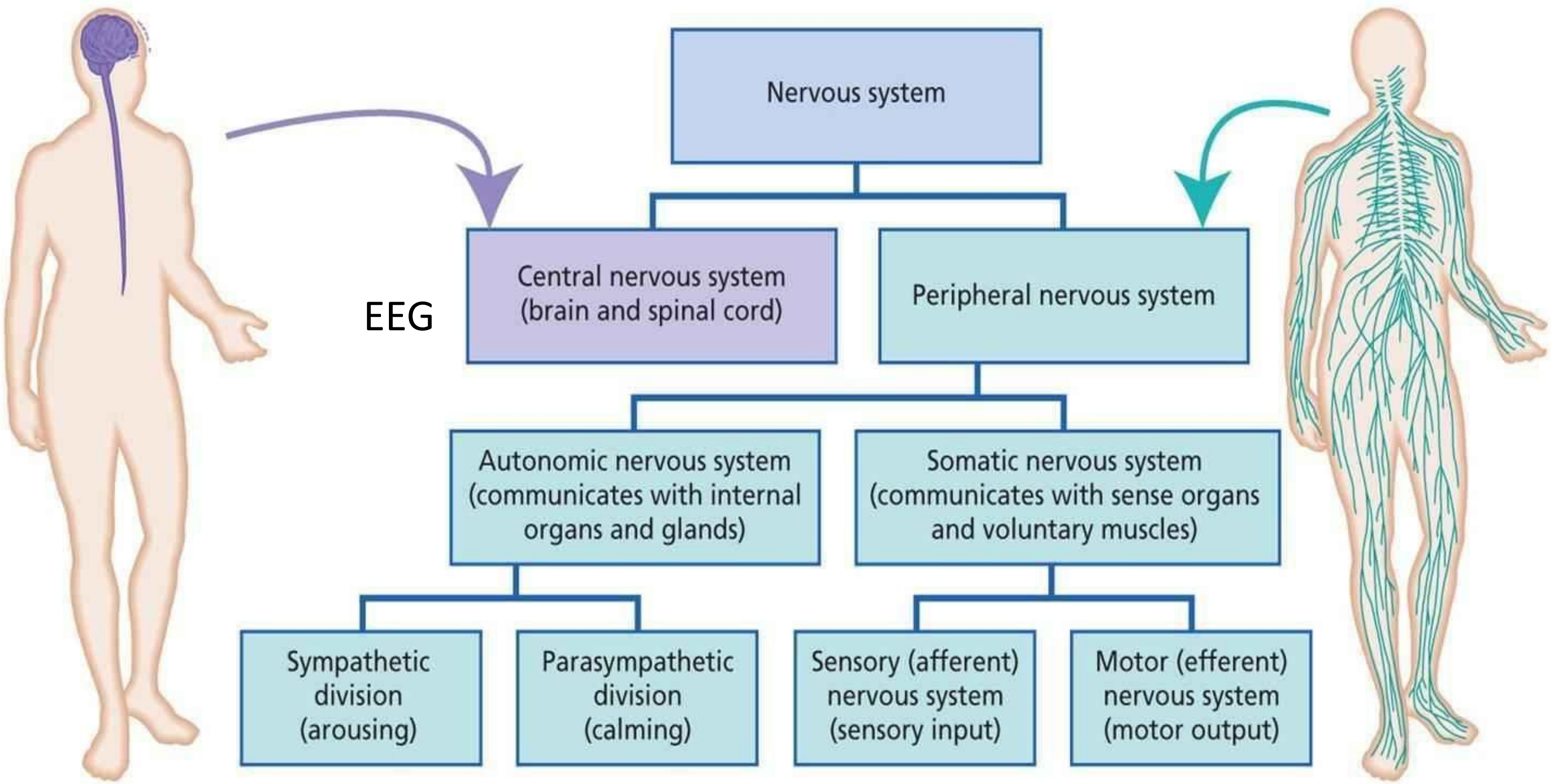
Perceived Stress Scale, Sheldon Cohen
http://www.mindgarden.com/documents/PerceivedStressScale.pdf

Self-reporting measures assessing “stress”

- **Multi-item questionnaires**
  - **Perceived Stress Scale (PSS):** e.g., PSS-14 / PSS-10 / PSS-4
    - **Variation of PSS: cStress used 5 items (scale 1-6):**
      - “Cheerful?”, “Happy?”, “Angry/Frustrated?”, “Nervous/Stressed?”, and, “Sad?”
  - **Positive and Negative Affect Schedule (PANAS)**
  - **Self assessment Manikin, State-Trait Anxiety Inventory and Stress** self rating scale are other questionnaires used to assess stress level, but generally show lower accuracies than PSS and PANAS
- **Single item questionnaire** for micro-EMA (e.g., using smart watches)
  - Correlation w/ (1) physiological stress (elicited), or (2) self-reported stress (PSS-4)
  - Correlation with physiological stress signals
    - **Were you stressed? - binary (correlation : 0.66)**
    - How stressed were you? - scale 0-6 (correlation : 0.63)
    - How worried were you? - scale 0-100 (correlation : 0.54)

micro-Stress EMA: A Passive Sensing Framework for Detecting in-the-wild Stress in Pregnant Mothers, IMWUT 2019

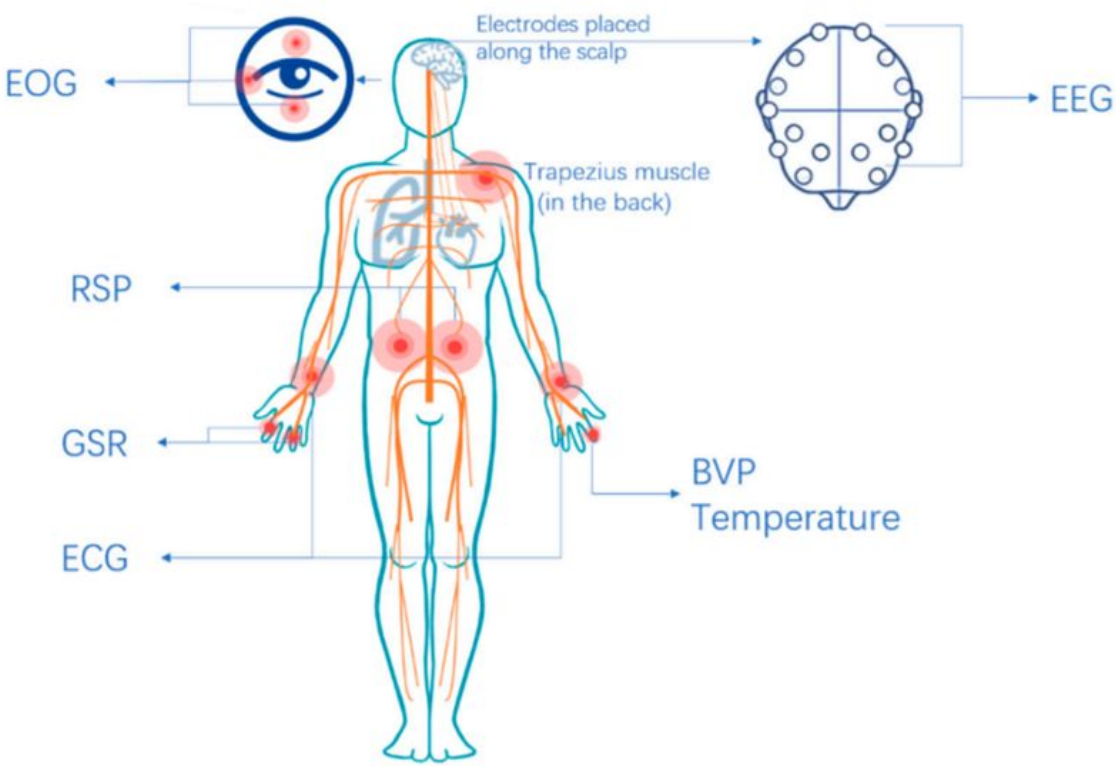
Sensing: Physiological Signals



ECG, EDA

EMG/EOG (Eyes) + Motion

Sensing: Physiological Signals



ECG	Electrocardiogram
PPG	Photoplethysmography
EDA	Electrodermal Activity (also known as Skin Conductance or Galvanic Skin Response)
RESP	Respiration (e.g., chest plethysmography)
EMG	Electromyography
EEG	Electroencephalography, also the source of event-related potentials (ERPs)
VOG	Video-oculography (eye tracking)
EOG	Electro-oculography
VID	Video-based posture/facial recognition
SPEECH	Speech recorded via microphone(s)
(ACL)	Accelerometer(s)
(BEHAV)	Behavioural data collected from device usage (e.g., mouse movements or driving controls)
(TOT)	Time-on-task
(CO2)	Capnography
(HSOUND)	Heart sound
(ICG)	Impedance cardiogram
(PRS)	Pressure (e.g., via piezoelectric sensors)
(SMM)	Sphygmomanometer (incl. proprietary tech such as Vasotrac)
(TEMP)	Thermometer (e.g., on finger or arm)

A Review of Emotion Recognition Using Physiological Signals, MDPI Sensors, 2016
Psychophysiology-based QoE Assessment: A Survey, 2016

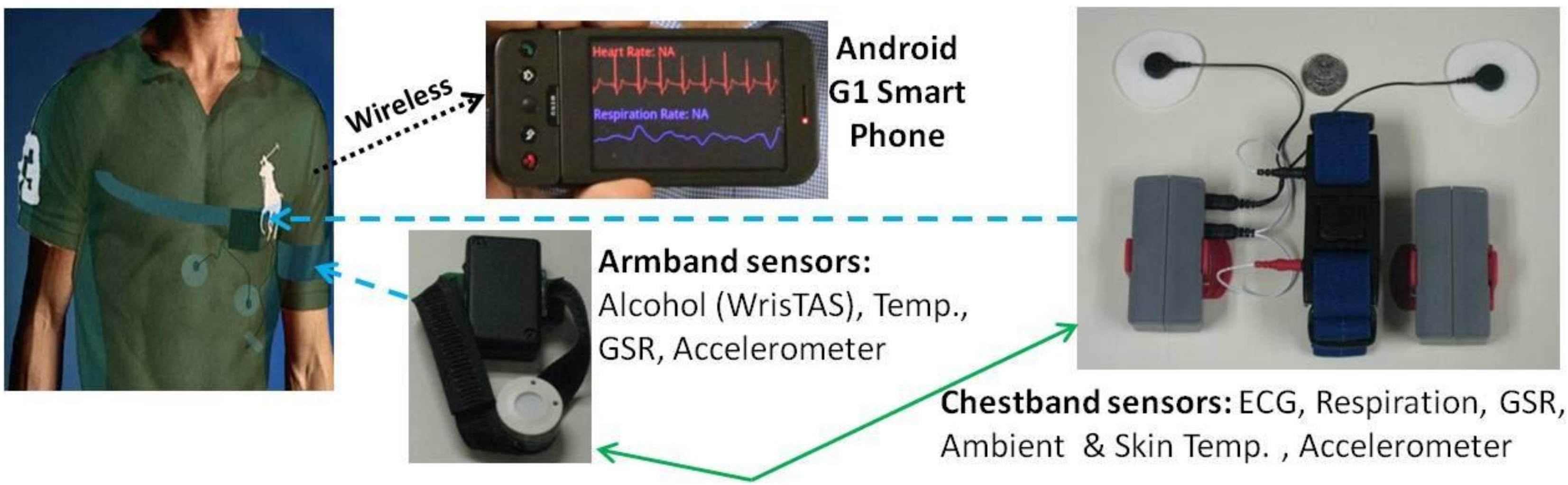
Agenda

- cStress: towards a gold standard for continuous stress assessment in the mobile environment, Karen Hovsepian, Mustafa al'Absi, Emre Ertin, Thomas Kamarck, Motohiro Nakajima, Santosh Kumar, September 2015 UbiComp '15
- MoodScope: Building a Mood Sensor from Smartphone Usage Patterns, Robert LiKamWa, Yunxin Liu, Nicholas D. Lane, Lin Zhong June 2013 MobiSys '13
- Daily Stress Recognition from Mobile Phone Data, Weather Conditions and Individual Traits, Andrey Bogomolov, Bruno Lepri, Michela Ferron, Fabio Pianesi, Alex (Sandy) Pentland, November 2014 MM '14
- DeepMood: Forecasting Depressed Mood Based on Self-Reported Histories via Recurrent Neural Networks, Yoshihiko Suhara, Yinzhan Xu, Alex 'Sandy' Pentland, WWW 2017

cStress: towards a gold standard for continuous stress assessment in the mobile environment

Karen Hovsepian, Mustafa al'Absi, Emre Ertin, Thomas Kamarck, Motohiro Nakajima, Santosh Kumar, September 2015 UbiComp '15

Sensing



https://sites.google.com/site/autosenseproject/

Stress Measurement: Lab vs. Field

- Lab: Stressors (stimulus approach)
  - Socio-evaluative stressor (speech)
    - for a given topic, asked to prepare (for 4 minutes) and deliver (for 8 minutes) a speech in front of a research staff
  - Cognitive stressor
    - given a three digit number and asked to add three digits of that number, and then add the sum to the three digit number
  - Physical stressor
    - asked to leave his/her hand submerged in ice cold water, for 90 seconds (with a break of follow-up 30 min rest period)
- Field: Everyday live situations (waking hours)
  - Participants will "naturally" experience "stress" while they perform everyday live activities (e.g., work)

Stress Measurement: Lab vs. Field

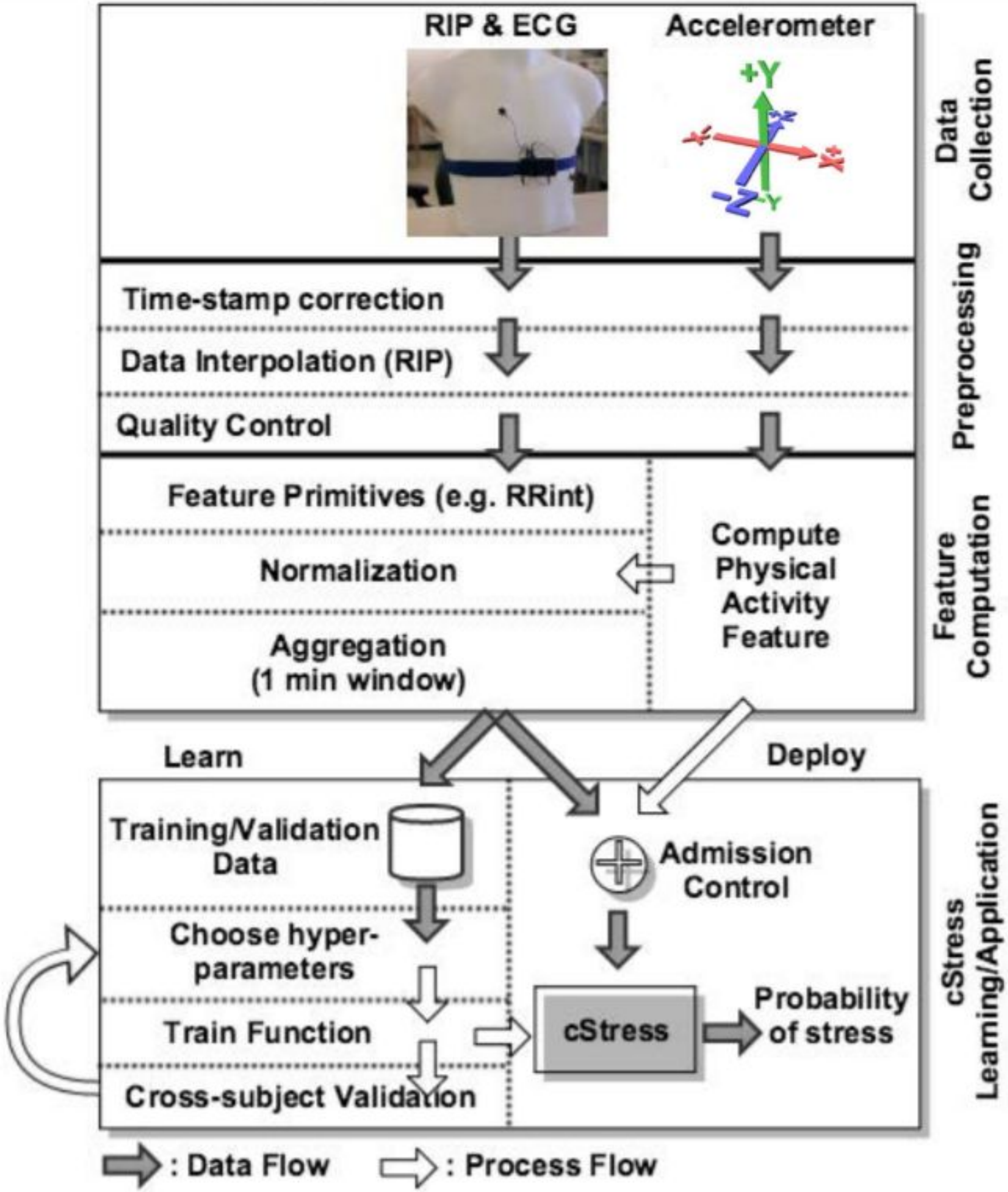
- Measuring stress via “5 item” self-reports
  - 6-point rating on emotion adjectives (similar to PANAS): “Cheerful?”, “Happy?”, “Angry/Frustrated?”, “Nervous/Stressed?”, “Sad?”
- In-lab study: asked to self-report before & after each stressor
- Field study: asked to self-report 15 times a day (probed at random point of time)
  - This random probing is known as an Ecological Momentary Assessment (EMA) or Experience Sampling Method (ESM)

Stress Measurement: Lab vs. Field

- Binarizing self-report scores
  - Average across all 5 stress items, reverse coding the two positive items (i.e., “happy” and “cheerful”)
  - Compute the mean of this quantity (i.e., score), for each participant, and use this mean as a threshold
  - For every score above the mean, classify the self-report as ”stressed”, and ”not stressed”, otherwise

Datasets

- Lab study
  - Elicitation+self-report on three cases (Socio-evaluative stressor (speech), Cognitive stressor, Physical stressor)
  - **Train dataset (n=24)**
  - **Test dataset (n=26)**
- Field study
  - **Field dataset (n=23)**
    - 23 participants wore the sensors for seven days in their natural field environment
  - Aiming to validate cStress in the much noisier real-life conditions against self-reported stress



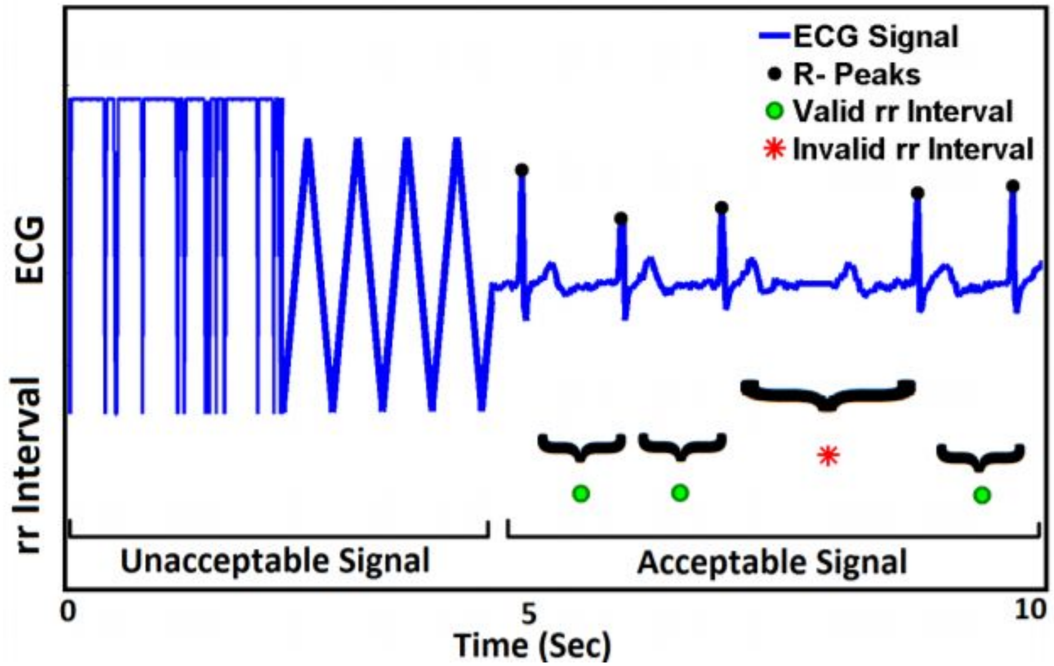
RIP & ECG
Accelerometer
+Y
-X
+X
-Z
-Y
Data Collection
Time-stamp correction
Data Interpolation (RIP)
Quality Control
Preprocessing
Feature Primitives (e.g. RRint)
Normalization
Aggregation (1 min window)
Compute Physical Activity Feature
Feature Computation
Learn
Deploy
Training/Validation Data
Choose hyper-parameters
Train Function
Cross-subject Validation
Admission Control
cStress
Probability of stress
cStress Learning/Application
: Data Flow
: Process Flow

Preprocessing

- Time synchronization issues
  - To maintain time synchronization among all the data collected, whether they are embedded on the phone (e.g., GPS, self-report) or coming from wireless sensors, each data packet is timestamped as soon as it is received on the phone
  - This introduces complications in maintaining accurate timestamps, especially if some packets are lost, or time-stamping process gets delayed due to buffer delays
  - Such irregular warping of packet inter-arrival times can degrade quality of features computed in the later steps
- Alignment
  - Minimize the sum of squared differences between the ideal timestamps (fixed sampling rate) and the actual timestamps
- Interpolation (missing value handling)
  - Cubic Hermite splines

Preprocessing

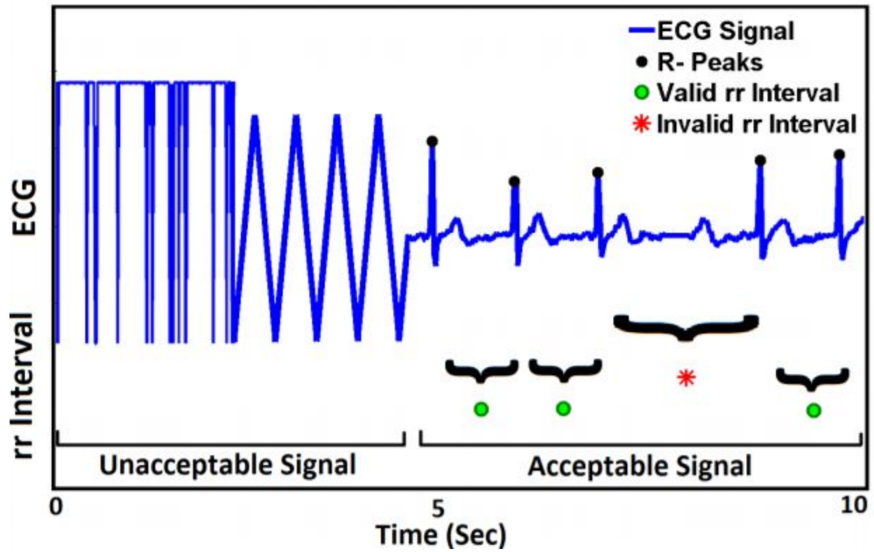
- Physical activity confounds



The portion of signal that holds ECG property marked as acceptable. The triangular shape and saturated at top is labeled unacceptable. Increased R-R interval due to missed R peaks are detected as invalid by the algorithm and marked with red dot.

Feature Extraction

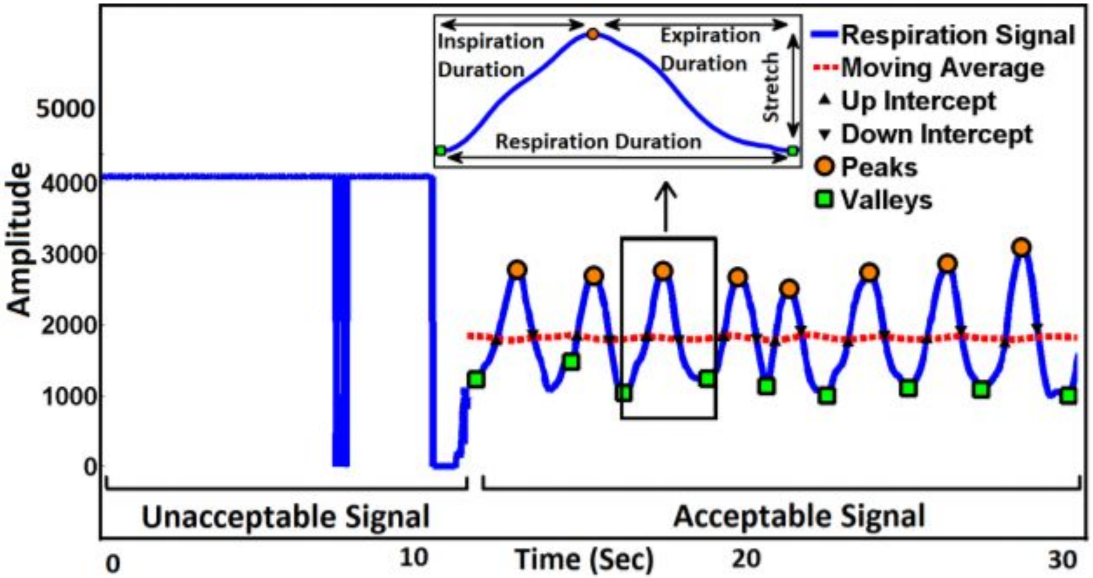
- ECG feature extraction steps:
  1. Identify the acceptable portions of an ECG signal
  2. Perform R-peak detection
  3. Calculate the difference between two consecutive R peaks is the R-R interval or inter beat interval (IBI)
  4. Remove outliers (knowledge based)
  5. Normalize R-R intervals (z-score)
     - Mean/variance estimates: winsorization (calculating after substituting extreme values; e.g., top/bottom 5%)



HRV	variance, quartile deviation, low frequency energy (0.1–0.2Hz), medium frequency energy (0.2–0.3Hz), high frequency energy (0.3–0.4Hz), low:high frequency energy ratio
non-HRV	mean, median, 80th percentile, 20th percentile, heart-rate

Feature Extraction

- RIP feature extraction



Empirical knowledge-based setting filtering: e.g., respiration duration varies 0.9 s – heavy exercise such as running to 12.5 s – light activity such as conversation and sitting

Base Features	Aggregations
inspiration duration, expiration duration, respiration duration, I:E duration ratio, stretch, respiratory sinus arrhythmia (RSA)[1]	mean, median, 80th percentile, quartile deviation

Model Training and Validation

- Support Vector Machines (SVM) w/ Kernel function
- Tuning hyper-parameters: C (margin) + γ (RBF) w/ grid search
- Validation
  - Cross-subject validation using “train dataset”
  - Out-of-sample validation
    - Model training with “train dataset”
    - Model testing with “test dataset”

Evaluation Results

- Cross-subject validation

			Accuracy				Optimal hyper-parameters		
Feature Set	F1	AUC	Hit-rate	TPR	FPR	C. Kappa	C	γ	$bias$
All	0.81	0.96	0.93	0.84	0.05	0.77	90.5097	0.000345267	0.339329
ECG	0.78	0.95	0.92	0.72	0.05	0.73	2	0.00552427	0.340407
HRV	0.56	0.78	0.84	0.55	0.1	0.46	724.077	0.0220971	0.250926
RIP	0.75	0.93	0.90	0.83	0.09	0.69	1448.15	0.000488281	0.308312

Table 3. Cross-subject validation performance metrics for dataset *train*

		Classified by Model		
		Stressed	Not stressed	Total
Actual	Stressed	236 (84%)	46 (16%)	282
	Not stressed	61 (5%)	1191 (95%)	1252
	Total	291	1237	1534

Table 4. Cross-subject validation confusion matrix for for dataset *train*

Evaluation Results

- Out-of-sample validation

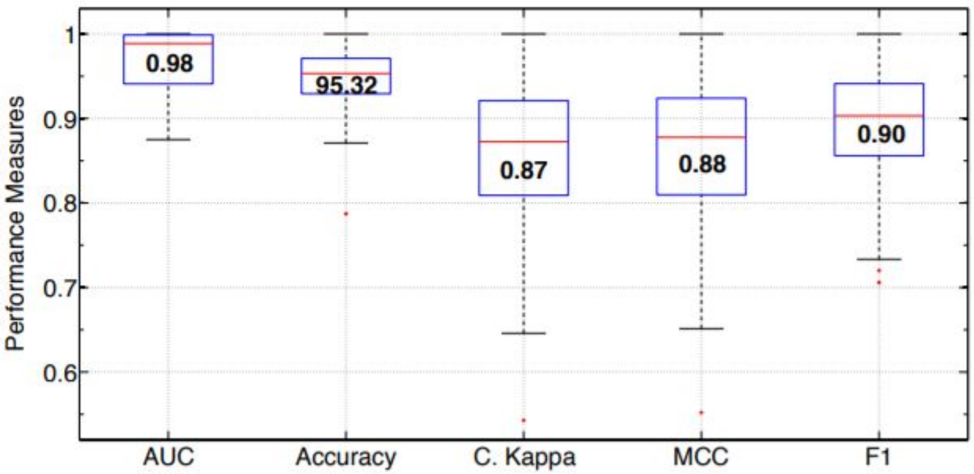
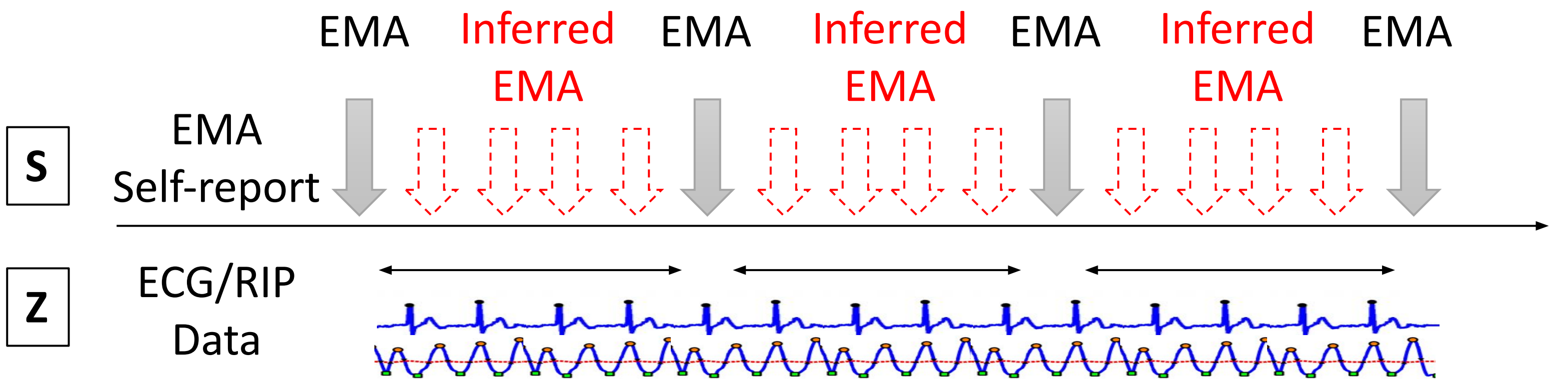


Figure 5. Box plots of AUC, Accuracy, Cohen's Kappa, Matthew's Correlation Coeffiecient (MCC), F1 score for all 26 the *test* cohort. Median values are displayed ins

		Classified By Model		
		Stressed	Not stressed	Total
Actual	Stressed	351 (89%)	45 (11%)	396
	Not stressed	56 (5%)	1149 (95%)	1205
	Total	407	1194	1501

Table 5. Test confusion matrix for dataset *test*, made by combining the confusion matrices for all test participants.

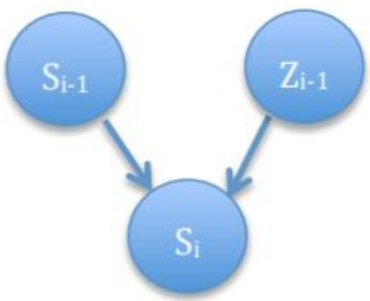
Lab => Field : Self-reported Stress Inference Model



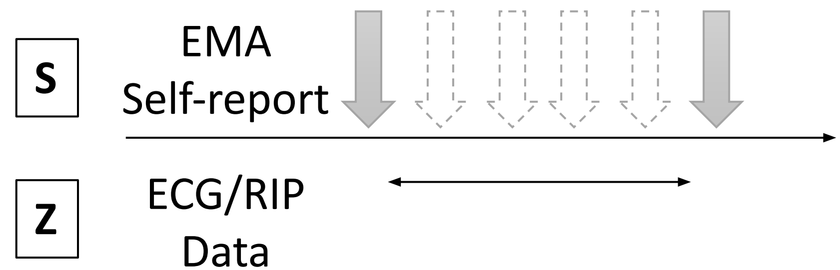
To allow for arbitrary lag between the physiological response captured by cStress and the memory of a stress event captured in self-report

Lab => Field : Self-reported Stress Inference Model

- Self-reported Stress Inference Model



		S_i	
S_{i-1}	Z_{i-1}	1	0
1	1	1	0
1	0	α	$1-\alpha$
0	1	β	$1-\beta$
0	0	0	1



Find α and β that maximize the F1 score of classifying all actual self-reports into either class 'stressed' or 'not stressed'

- S_{i-1}: self-reported stress for minute i-1 (inferred)
- Z_{i-1}: physiological stress arousal for minute i-1 (sensor-based estimation)
- All three variables are binary, valued as 1 ('stressed') or 0 ('not stressed')

Bayesian Network model of self-reported stress

Lab => Field : Self-reported Stress Inference Model

- Self-reported Stress Inference Model

	train	*field*
Median F1	0.75	0.71
Median AUC	0.85	0.60
Median Accuracy	0.9	0.72

Table 6. Median self-reported stress inference results, across all participants, for *train* and *field* cohorts.

- To learn the model, we use a grid-search for α and β that maximize the F1 score of classifying all actual self-reports into either class 'stressed' or 'not stressed'.
- To compute the F1 score, we need the probabilities $p(S_i = 1)$, computed using equations (1) and (2), and the ground truth labels for S_i , which can be computed from the EMA self-report scores, by quantizing them into binary 'stressed'/'not stressed' labels.

MoodScope: Building a Mood Sensor from Smartphone Usage Patterns

Robert LiKamWa, Yunxin Liu,
Nicholas D. Lane, Lin Zhong June 2013 MobiSys '13

Mood Journaling

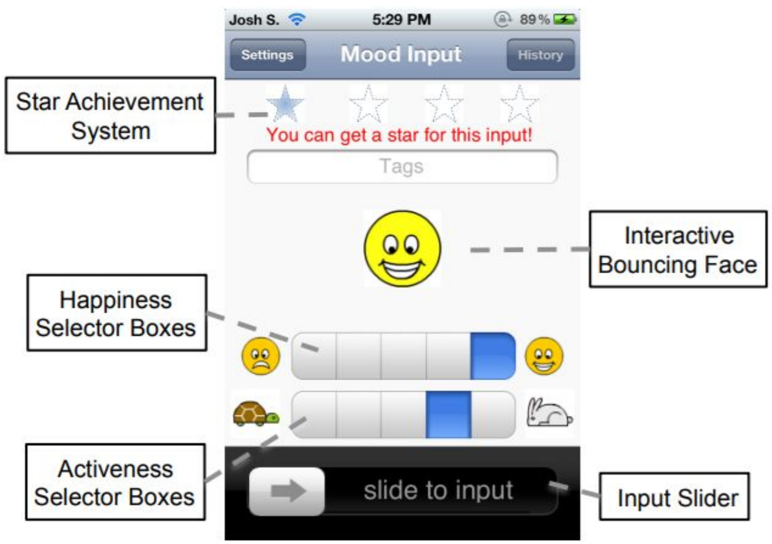


Figure 2: Mood journaling application view

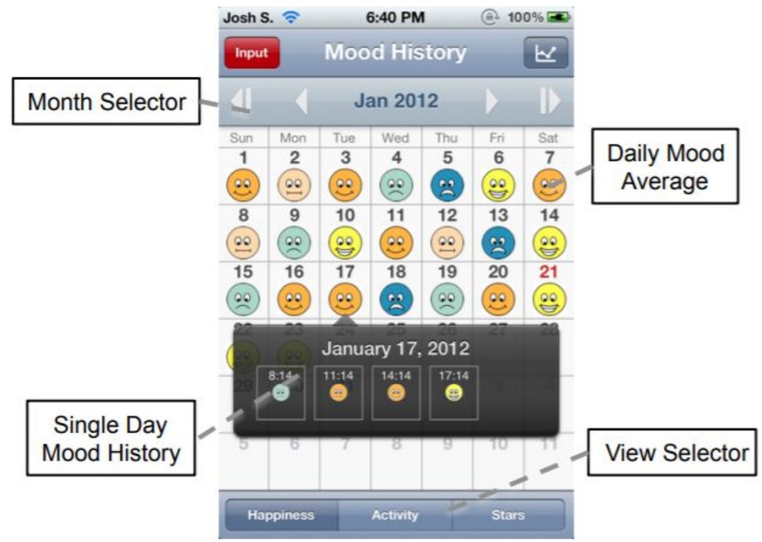


Figure 3: Mood calendar application view

This logged data is used to predict daily average mood

Feature Extraction

Table 1: Feature table of usage histograms (and previous mood averages)

Data Type	Histogram by:	Dimensions
Email contacts	# Messages	10
	# Characters	10
SMS contacts	# Messages	10
	# Characters	10
Phone call contacts	# Calls	10
	Call Duration	10
Website domains	# Visits	10
Location Clusters	# Visits	10
Apps	# App launches	10
	App Duration	10
Categories of Apps	# App launches	12
	App Duration	12
Previous 2 Pleasure and Activeness Averages	N/A	4

Mood Prediction

- Multiple regression w/ feature selection
- Personalized models: per person model building
- All-user model: single model w/ all user data
- Hybrid model:
  - Combine a small amount of user-specific training data with larger amounts of training data collected from the general user population
  - Modified objective function that prioritizes reducing residual errors related to personalized training data above errors related to training data sourced from the rest of the population
- Leave-One-Out-Cross-Validation (LOOCV)

Evaluation Results

Model	Pleas. MSE	Pleas. Acc.	Activ. MSE	Activ. Acc
Model A: average mood	0.242	73%	0.229	74%
Model B: slow-varying mood	0.354	61%	0.318	65%
Model C: no phone features	0.258	70%	0.277	71%
All-user Model	0.296	66%	0.289	67%
Personalized Model	0.075	93%	0.085	93%

pleasure and **activ**eness dimensions

Daily Stress Recognition from Mobile Phone Data, Weather Conditions and Individual Traits

Andrey Bogomolov, Bruno Lepri, Michela Ferron,
Fabio Pianesi, Alex (Sandy) Pentland, November 2014
MM '14

Daily Stress Recognition

- The goal of this paper was to investigate the automatic recognition of people's daily stress from three different sets of data:
  - a) people activity, as detected through their smartphones (data pertaining to transitory properties of individuals);
  - b) weather conditions (data pertaining to transitory properties of the environment); and
  - c) personality traits (data concerning permanent dispositions of individuals)

Data Collection

- From November 12, 2010 to May 21, 2011, we collected a dataset capturing the lives of 117 subjects living in a married graduate student residency of a major US university
- During this period, each participant was equipped with an Android-based cellular phone incorporating a sensing software explicitly designed for collecting mobile data.
- Such software runs in a passive manner and does not interfere with the every day usage of the phone.
- The data collected consisted of:
  - (a) call logs, (b) sms logs, (c) proximity data, obtained by scanning near-by phones and other Bluetooth devices every five minutes
  - (d) data from surveys administered to participants, which provided self-reported information about personality traits ("Big Five") and self reported information about **daily stress (Ground Truth)**

Feature Extraction

General Phone Usage
1. Total Number of Calls (Outgoing+Incoming)
2. Total Number of Incoming Calls
3. Total Number of Outgoing Calls
4. Total Number of Missed Calls
5. Number of SMS received
6. Number of SMS sent
Diversity
7. Number of Unique Contacts Called
8. Number of Unique Contacts who Called
9. Number of Unique Contacts Communicated with (Incoming+Outgoing)
10. Number of Unique Contacts Associated with Missed Calls
11. Entropy of Call Contacts
12. Call Contacts to Interactions Ratio
13. Number of Unique Contacts SMS received from
14. Number of Unique Contacts SMS sent to
15. Entropy of SMS Contacts
16. Sms Contacts to Interactions Ratio
Active Behaviors
17. Percent Call During the Night
18. Percent Call Initiated
19. Sms response rate
20. Sms response latency
21. Percent SMS Initiated
Regularity
22. Average Inter-event Time for Calls (time elapsed between two events)
23. Average Inter-event Time for SMS (time elapsed between two events)
24. Variance Inter-event Time for Calls (time elapsed between two events)
25. Variance Inter-event Time for SMS (time elapsed between two events)

General Bluetooth Proximity
1. Number of Bluetooth IDs
2. Times most common Bluetooth ID is seen
3. Bluetooth IDs accounting for n% of IDs seen
4. Bluetooth IDs seen for more than k time slots
5. Time interval for which a Bluetooth ID is seen
6. Entropy of Bluetooth contacts
Diversity
7. Contacts to interactions ratio
Regularity
8. Average Bluetooth interactions inter-event time (time elapsed between two events)
9. Variance of the Bluetooth interactions inter-event time (time elapsed between two events)

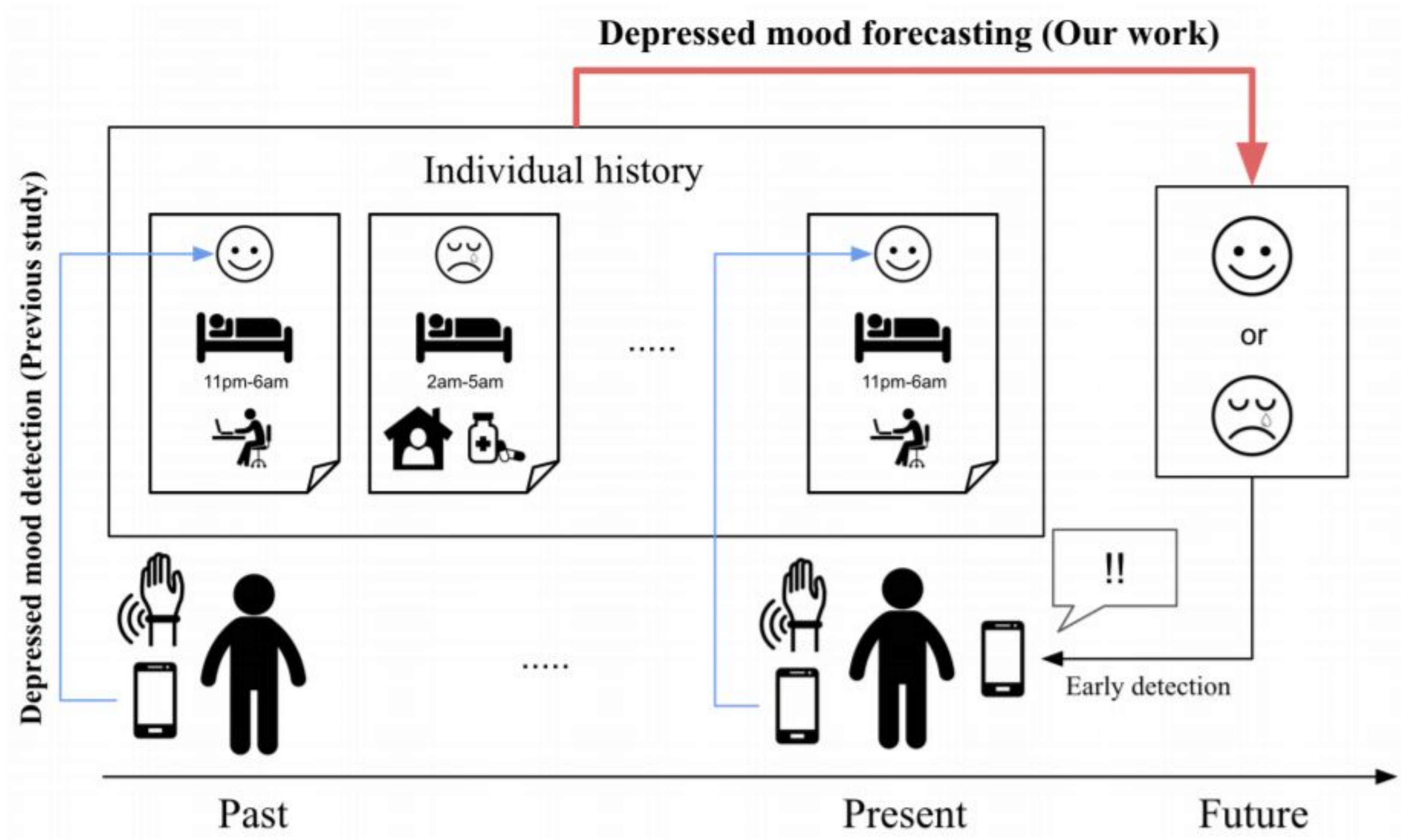
Ranked Features

Rank	Feature
1	personality.Conscientiousness
2	personality.Agreeableness
3	personality.Neuroticism
4	personality.Openness
5	personality.Extraversion
6	weather.MeanTemperature
7	sms.RepliedEvents.Latency.Median
8	weather.Humidity
9	sms.AllEventsPerDay
10	bluetooth.Q95TimeForWhichIdSeen
11	bluetooth.MaxTimeForWhichIdSeen
12	sms.IncomingAndOutgoingPerDay
13	weather.Visibility
14	weather.WindSpeed
15	bluetooth.Q90TimeForWhichIdSeen
16	bluetooth.TotalEntropyShannon
17	call.EntropyMillerMadowOutgoingTotal
18	call.EntropyShannonOutgoingAndIncomingTotal
19	bluetooth.TotalEntropyMillerMadow
20	bluetooth.IdsMoreThan09TimeSlotsSeen
21	bluetooth.IdsMoreThan04TimeSlotsSeen
22	call.EntropyShannonMissedOutgoingTotal
23	bluetooth.IdsMoreThan19TimeSlotsSeen
24	call.EntropyShannonOutgoingTotal
25	bluetooth.Q75TimeForWhichIdSeen
26	call.EntropyMillerMadowMissedOutgoingTotal
27	call.EntropyMillerMadowOutgoingAndIncomingTotal
28	sms.OutgoingAndIncomingTotalEntropyMillerMadow
29	sms.OutgoingTotalEntropyMillerMadow
30	bluetooth.Q50TimeForWhichIdSeen
31	bluetooth.Q68TimeForWhichIdSeen
32	sms.OutgoingTotalEntropyShannon

DeepMood: Forecasting Depressed Mood Based on Self-Reported Histories via Recurrent Neural Networks

Yoshihiko Suhara, Yinzhan Xu, Alex 'Sandy' Pentland, WWW 2017

Mood forecasting task



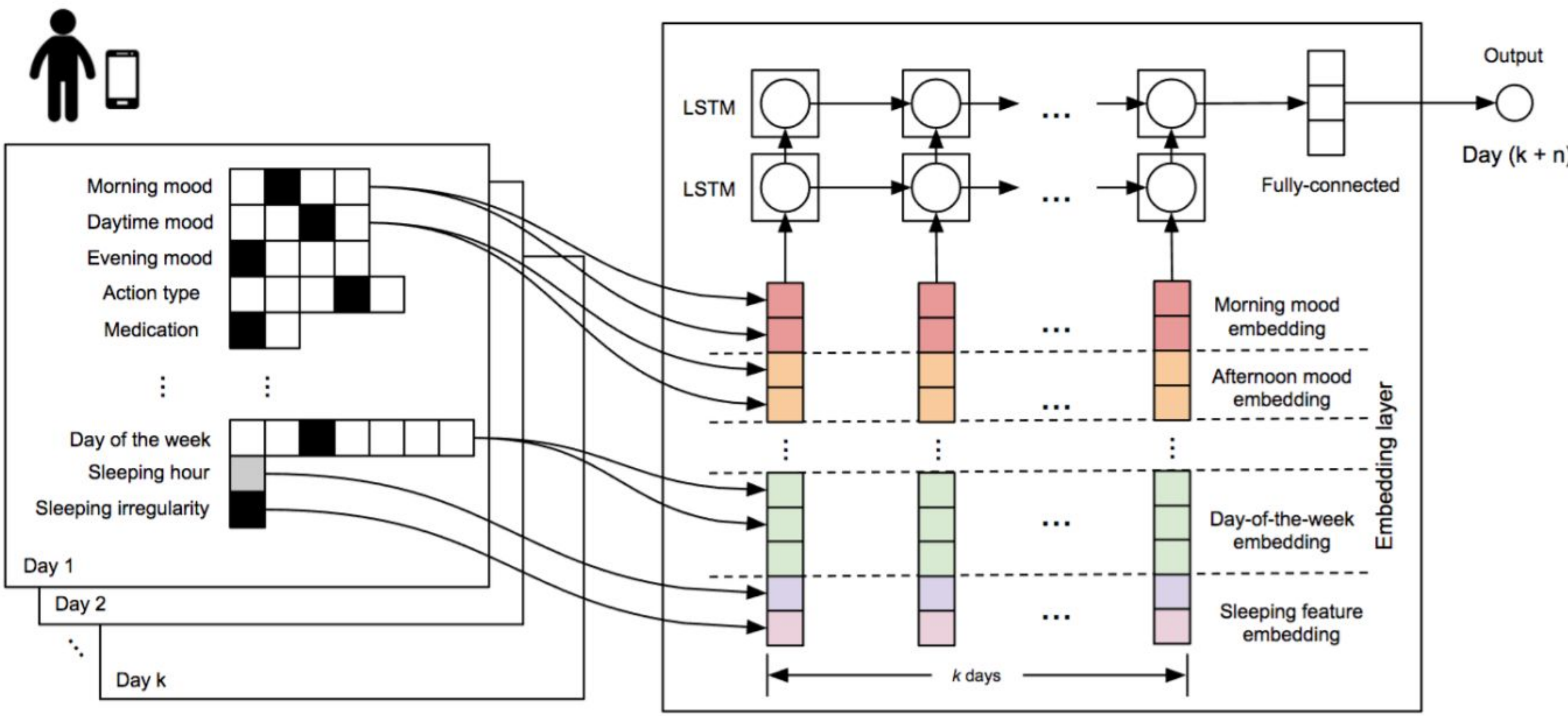
(a) (b) (c)

Figure 2: Screenshots of the application used for collecting self-reported histories. (a) The application provides users with a single-tap interface to report moods and action types throughout the day. (b) Users can also submit sleeping times (bedtime, wake-up time) in a similar manner. (c) The application visualizes a user's history to look back the user's mood transition and maintain his or her motivation for using the application.

Logged data

Category	Name	Value type
Mood	Morning mood	{fine, fair, depressed, irritated}
	Afternoon mood	
	Evening mood	
Behavioral log	Action type	{Go to work, go outside, work at home, do nothing at home, sick in bed}
	Medication	{yes, no}
	Urgent medication	{yes, no}
	Hospital attendance	{yes, no}
Sleeping log	Bedtime	HH:MM
	Wake-up time	HH:MM
	Nocturnal awakening	{yes, no}
	Taking a nap	{yes, no}

Model Building (LSTM)



Dataset

Total days	345,158
Number of users	2,382
Avg. days / user	144.9
Number of severe / Nonsevere labels	32,205 / 312,953

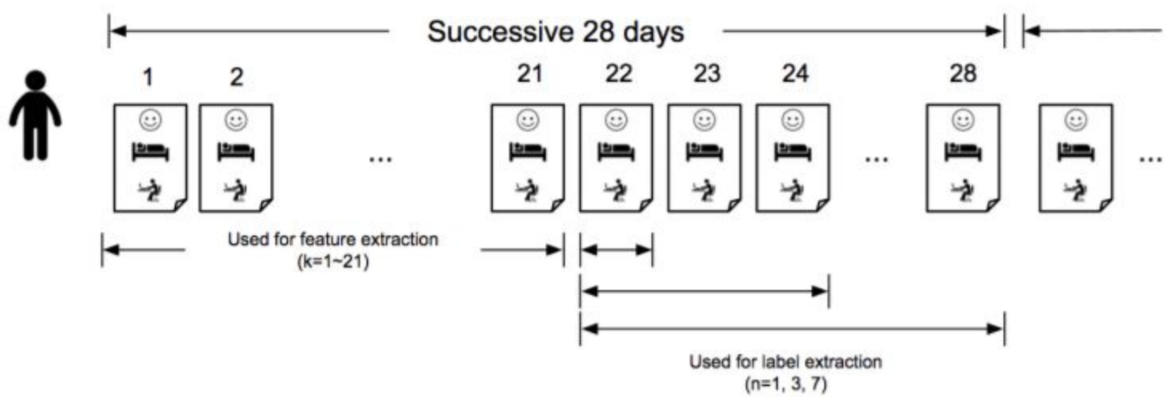


Figure 7: Instance extraction from a user's histories. Each block (instance) contains successive 28 days without overlapping with other instances.

Evaluation Results

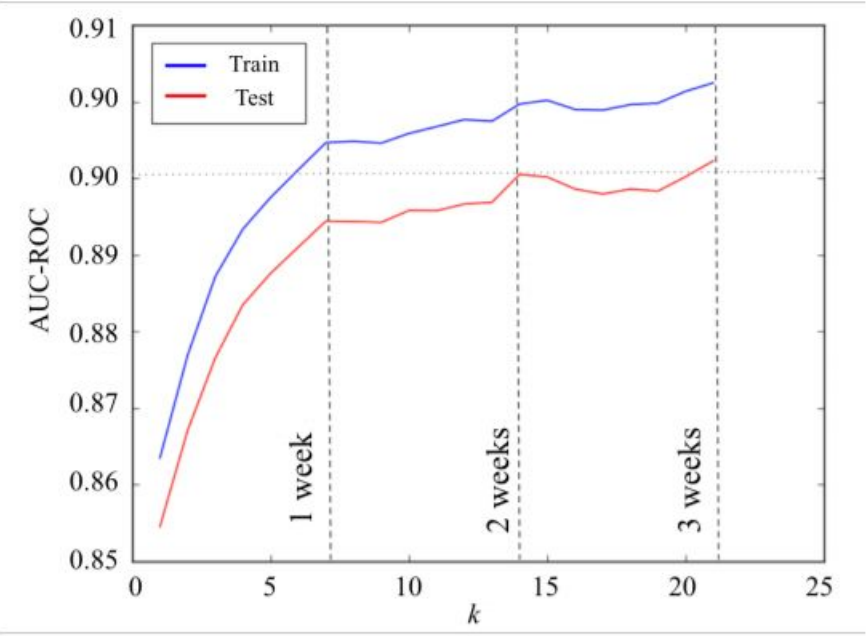


Figure 9: Forecasting performance over different days used for training. The x-axis denotes the number of days used for the model and the y-axis denotes the AUC-ROC values.

Backup slides

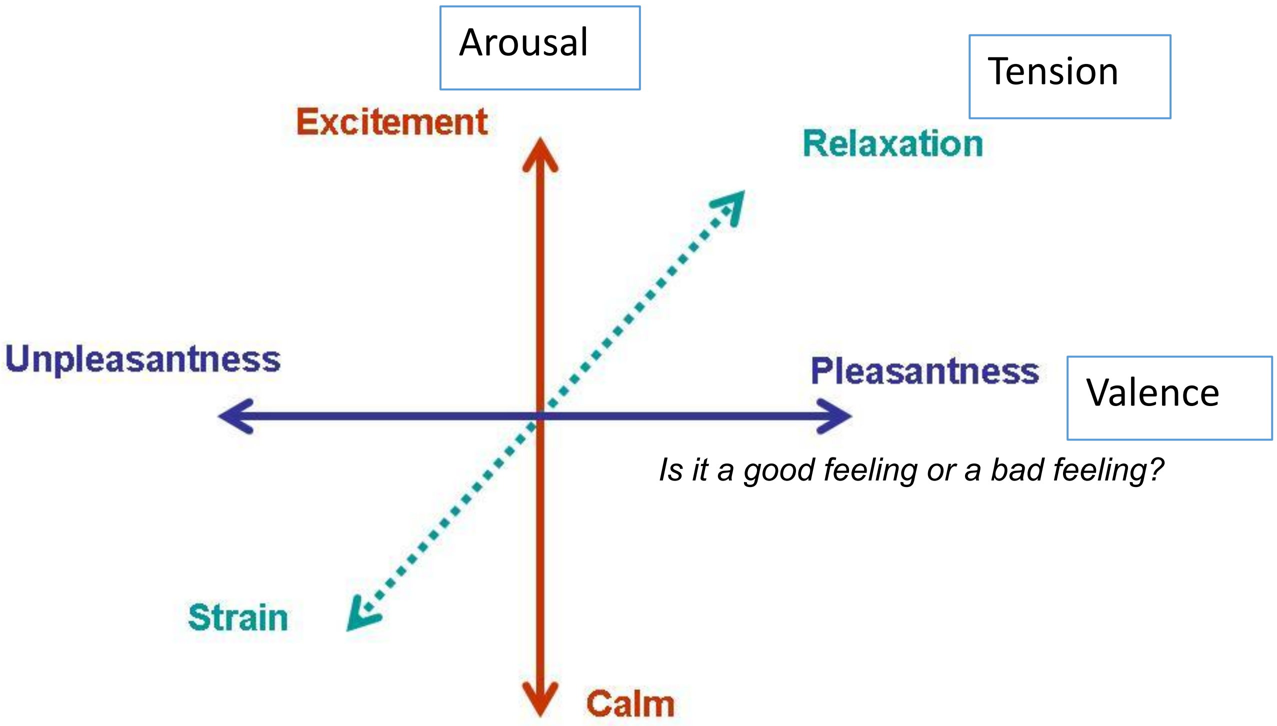
Emotion

- Emotions have been defined as "brief, multicomponent, largely automatic psychological mechanisms that coordinate a variety of cognitive, physiological, and motor processes, facilitating an adaptive response to particular kinds of fitness-relevant opportunities or threats" (Shiota et al., 2017)
- A more succinct definition of *emotion* is as "brief, adaptive responses, involving physiological and cognitive reaction to objects, people, or situations" (Niedenthal et al., 2006)
- Yet another is as "A multicomponent response to a challenge or opportunity that is important to an individual's goals" (Oakley et al., 2006)
- Currently no scientific consensus on a definition
- Emotion is often intertwined with mood, personality, disposition, and motivation

https://www.ocf.berkeley.edu/~jfkihlstrom/IntroductionWeb/emotion_supplement.htm

Emotion

- Decomposing the emotion space along three axes (Wilhelm Wundt, 1899)



Basic emotion

- Schwartz, Shaver, O'Connor (1987)
  - **Love**, including such terms as *liking* and *passion*.
  - **Happiness**, including such words as *joy* and *ecstasy*.
  - **Anger**, including such terms as *frustration*, *rage*, *resentment*, *disgust*, and *envy*.
  - **Sadness**, including such words as *agony*, *grief*, *disappointment*, *guilt*, *loneliness*, and *pity*.
  - **Fear**, including such words as *alarm*, *fright*, and *anxiety*.

Shaver, P., Schwartz, J., Kirson, D., & O'Connor, C. (1987). Emotion knowledge: Further exploration of a prototype approach. *Journal of Personality and Social Psychology, 52*(6), 1061-1086.

27 Varieties of Emotional Experience (Arranged Alphabetically)

1. Admiration
2. Adoration
3. Aesthetic Appreciation
4. Amusement
5. Anger
6. Anxiety
7. Awe
8. Awkwardness
9. Boredom
10. Calmness
11. Confusion
12. Craving
13. Disgust
14. Empathic Pain
15. Entrancement
16. Excitement
17. Fear
18. Horror
19. Interest
20. Joy
21. Nostalgia
22. Relief
23. Romance
24. Sadness
25. Satisfaction
26. Sexual Desire
27. Surprise

- UC Berkeley's Alan Cowen and Dacher Keltner (*PNAS* 2017)
  - Asked people to rate their emotional responses to more than 2,000 video clips (recruited via M-Turk)

Self-report captures 27 distinct categories of emotion bridged by continuous gradients, Alan S. Cowen and Dacher Keltner, PNAS 2017 https://s3-us-west-1.amazonaws.com/emogifs/map.html#