

# Social and sentiment sensing and assisting using on-body sensors

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## Topic, objectives and justification of the project

Emotional states are closely linked to Physical health [42], such as anger, which increases the danger of heart disease [49] or mood which impacts health-relevant behavior, aging and can also act as a predictor of mortality [50]. In addition, mental health is linked to emotion regulation [23], whereas stress, especially when pertaining, has significant impact on brain, cognition and work performance [31]. On the other hand, positive affect benefits the immune system [49] while happiness and satisfaction are good indicators for work performance, health, and also success in private life [32].

Sentiment and emotion can be detected from Physiological signals with sensors such as Electromyograms (EMG, muscle activity), Electrodermal Activity (EDA, electrical conductivity of the skin surface), Electrocardiogram (EKG or ECG, heart activity), Electrooculogram (EOG, eye movement) or Electroencephalography (EEG, brain activity) [9]. These kind of sensors, however, are accessible only to a small share of the population and have drawbacks such as high cost, weight, non-portability, and sometimes involve invasive implantation.

Recent work shows that it is also possible to detect sentiment from gesture and pose [16]. With the verge of the Internet of Things and increasing amount of mobile and body worn devices and sensors in everyday life, a multitude of sensors is available nowadays which has the potential to capture body movement and pose.

The focus and contribution of this project is to (1) recognise emotion from medical sensors, (2) exploit the potential of cheaper smartphone and on-body IoT sensors for sentiment sensing by identifying correlations in sensor data traces with medical sensors, (3) exploit environmental signals such as RSSI or RF-signal strength for sentiment sensing, (4) predict the evolution of sentiment from the time series of past observations,

(5) develop memory, time, and computation efficient methods to perform such analysis on a smartphone and, (6) develop and experiment with sentiment feedback methods.

The outcome of the project will be a sentiment sensing and feedback framework comprising medical, body, smartphone and environmental sensors together with a prototype implementation

## **Current state-of-the-art in an international perspective**

Emotion research or affective science investigates affect expression and detection [9]. In this context, the recognition of emotion has been considered from facial expressions [20], voice [25] as well as body language and posture [35, 19]. Especially the latter is of greater interest for this project and is discussed below. There is also some body of work on utilizing text mining for sentiment sensing as briefly discussed in the next section.

### **Sensing of sentiment from textual corpus**

Sentiment mining is an active research topic in recent years [27, 10]. Also referred to as opinion mining, it considers indirect sources and requires actual active involvement of subjects [36, 60]. In particular, there is an active body of work in the direction of mining textual input (via sentiment-expressing words or phrases) in online social networks with the help of natural language processing and computational linguistics [30]. We will, however, not consider the mining of text in the scope of this project but rather focus on sentiment sensing from physical sensors. Nevertheless, if necessary, we may exploit textual input to better tune the parameters of our sensor-based sentiment analyzer.

### **Sentiment sensing from body movement and pose**

Emotion can be inferred from body gesture and pose [24] at least as accurately as from face [4, 12, 33]. The role of human body in emotion expression has received support through evidences from psychology [54] and nonverbal communication [18]. The importance of bodily expression has also been confirmed for emotion detection [53, 51, 5]. Walter and Walk [54] revealed that emotion recognition from photos of postural expression, in which faces and hands were covered, was as accurate as recognition from facial expression alone. Dynamic configurations of human body even hold greater

amount of information as indicated by Bull in [8]. He proved that body positions and motions could be recognised in terms of states including interest/boredom and agreement/disagreement. Some other studies went further by looking for the contribution of separated body parts to particular emotional states [16, 34]. Emotion can be recognised from non-trivial scenarios, such as simple daily-life actions [15, 7] or recognition ability of infants [28].

Researchers [35, 19], were able to detect boredom, confusion, delight and frustration utilizing pressure mats. Such mats are not portable and thus are not applicable in our setting. Instead, we aim to detect sentiment from body- or environmental sensors.

Additionally, the sensing of attention has been investigated previously. Attention is an important measure in Computer-Human interaction. It determines for an interactive system the potential to impact the actions and decisions taken by an individual [58]. In the literature, we find various definitions that classify attention as well as its determining characteristics [57, 55]. While the tracking of gaze is a commonly utilized measure of attention [59], also other observable features may indicate attention. In general, aspects such as saliency, effort, expectancy and value are important indicators of attention [56, 55, 58, 22]. This model was later extended to put a greater stress on the effort a person takes towards an object [21]. The authors also discuss various aspects of attention and identify as most distinguishing factors changes in walking speed, direction or orientation.

Shi et al [43] investigated how these properties, in particular location of a person, walking direction and walking speed or changes therein can be utilized for the monitoring and detection of attention from fluctuation in received signal strength.

## **Sensing activity, motion and pose from inertial and environmental sensors**

Activity recognition comprises the challenge to recognize human activities from the input of sensor data. Traditionally, acceleration has evolved as the standard modality for activity recognition both for high diffusion and convincing recognition rates [41, 11]. General research challenges for activity recognition regard the accurate classification of noisy data captured under real world conditions [6] or the automation of recognition systems [39]. The classification accuracy is highly dependent on the accurate sensor placement. The integration of sensors in clothing as well as the recent remarkable progress in the robustness to rotation or displacement have improved this situation greatly [13].

We will in addition consider environmental sources, in particular signal strength information from WiFi or 2-3G systems for their ubiquitous availability. In particular, good

accuracy has been achieved recently with systems exploiting fluctuation in received radio signals. Pu and others [40, 26] showed that simultaneous detection of gestures from multiple individuals is possible by utilizing multi-antenna nodes and micro Doppler fluctuations. They utilize a USRP SDR multi antenna receiver and one or more single antenna transmitters distributed in the environment to distinguish between a set of 9 gestures with an average accuracy of 0.94. Their active device-free system exploits a MIMO receiver in order to recognise gestures from different persons present at the same time. By leveraging a preamble gesture pattern, the receiver estimates the MIMO channel that maximises the reflections of the desired user.

A main challenge was for them that the Doppler shift from human movement is several magnitudes smaller than the bandwidth of the signal employed. The authors therefore proposed to transform the received signal into several narrowband pulses which are then analysed for possible Doppler fluctuation. The group recently discussed application possibilities of their system [1].

In a related system, Adib and Katabi [3] employ MIMO interference nulling and combine samples taken over time to achieve a similar result while compensating for the missing spatial diversity in a single-antenna receiver system. In their system, they leverage standard WiFi hardware at 2.4GHz.

Later, this work was extended to 3D motion tracking by utilizing three or more directional receive antennas in exactly defined relative orientation [2]. In particular, the system is able to track the center of a human body with an error below 21cm in any direction and can also detect movement of body parts and directions of a pointing body part, such as a hand. This localisation is possible through time-of-flight estimation and triangulation. Higher accuracy of this estimation is granted by utilizing frequency modulated carrier waves (sending a signal that changes linearly in frequency with time) over a bandwidth of 1.69GHz. Impact of static objects could be mitigated by subtracting successive sample means whereas noise was filtered by its speed of changes in energy over frequency bands.

## **Research approach, methods and hypotheses**

We plan to apply a machine learning approach in which prediction and feedback tools are built based on data. Specifically, we plan to install and employ a wide range of sensors, some on-body, some are already installed on everyday smartphones, and some are located in an environment. We will collect data from these sensors and analyse

it, where the goal is to find a small, cheap and efficient subset of sensors which provides a robust and stable signal for prediction. Next, we will build a prediction system of sentiment based on this signal. We will use the collected signals and true sentiment to generate a predictive model of sentiment from the signal. We will test the model on signals coming from participants of our study. We will also develop a feedback algorithm that will provide user information about current sentimental state, and possibly future predicted one. Hopefully, the user will benefit from such feedback. Additional components we plan to pursue is the development of efficient prediction and feedback methods, that could be executed on a smartphone.

We hypothesize that we will be able to collect sensor information of users, and their true or approximated sentimental state. We also assume that it is possible to predict sentiment from signals of sensors. Both assumptions are reasonable as similar tasks were already performed by both PIs in other contexts.

## **Detailed work programme including time schedule**

The expected time schedule is depicted in table 1. A detailed description of the distribution of work packages to personnel is given in the following. The figures represent three person months (equal to one person quarter). The notation '40' represents an allocation of 40 percent of one person quarter.

### **WP-1: Review of recent advances in sentiment recognition**

Estimated effort 6 PM

Precondition –

Milestone *Follow-up related work and recent developments*

In this workpackage we will follow up recent developments focusing sentiment sensing and opinion mining. This ongoing task is distributed over the whole project duration.

### **WP-2: Development of sentiment sensing systems**

#### **WP-2.1: Development of the basic recognition system**

Estimated effort 3 PMs

Precondition –

Milestone *Sentiment sensing system with interfaces for various sensor types*

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	
Recent advances WP-1	25	25	20	20	20	20	20	15	10	10	10	5	200
Sensing system WP-2.1	100												100
WP-2.2	50	50											100
WP-2.3	25	75											100
WP-2.4		50	50										100
WP-2.5				30	30	40							100
Experiments WP-3.1			130	70									200
WP-3.2							50	30	30	45	30	15	200
WP-3.3									60			40	100
Analysis WP-4.1				80	20								100
WP-4.2					130	70							200
WP-4.3						70	130						200
WP-4.4								100	55	45			200
WP-4.5										50	100	50	200
Prediction WP-5.1								55	45				100
WP-5.2										50	60	90	200
Sum	200	200	200	200	200	200	200	200	200	200	200	200	2400

Table 1: Occupation (1PM) subject to the quarterly period and project task.

In this workpackage we develop a sensing system to attach medical, body, smartphone and environmental sensors. The system will comprise interfaces for various sensing sources and cover of mobile clients to collect data samples and a server backend where the data is collected and processed. We perform preliminary analysis of the data collected from various sources to evaluate various aspects of them, such as, robustness, noise, and redundancy.

## WP-2.2: Integration of medical sensing equipment

Estimated effort 3 PMs

Precondition WP-2.1

Milestone *Integration of medical sensor equipment to the sensing system*

In this workpackage we integrate medical sensors (EMG and EOG) with the developed framework. We will have access to the medical sensors via a cooperation with the medical center at Georg-August University Goettingen, in particular with the Neurohabilitation Engineering Group of Professor Dario Farina<sup>1</sup>. We will develop methods to predict the

<sup>1</sup><http://www.nre.bccn.uni-goettingen.de/index.php?id=82>

output of the medical sensors from smartphone and other sensors in WP-4.2 for the use in our sentiment prediction system.

### **WP-2.3: Integration of smartphone and body sensors**

Estimated effort 3 PMs

Precondition WP-2.1

Milestone *Integration of smartphone and body sensors to the sentiment sensing system*

In this workpackage we integrate smartphone and body sensors with the developed framework. Our focus will be on the integration of acceleration data from smartphones and sensor nodes. In particular, we will utilize INGA<sup>2</sup> sensor nodes to which we have access through a cooperation with TU Braunschweig, Germany. In addition, heart rate and accelerometer sensors, for instance, from fitness wristbands will be incorporated. We will evaluate the amount of sensor information such that we will be able to minimize usage of the phone's resource, and extend battery life.

### **WP-2.4: Integration of environmental sensors**

Estimated effort 3 PMs

Precondition WP-2.1

Milestone *Integration of USRP software radio nodes to the sensing system*

In this workpackage we integrate USRP<sup>3</sup> devices with the developed framework. For this, we can utilize 8 fully equipped USRP-1 devices and transceivers for the 800 MHz range available at the chair for Computer networks at Georg-August U. Goettingen.

### **WP-2.5: Development of a mobile sensing system for continuous sampling**

Estimated effort 3 PMs

Precondition WP-2.1, WP-2.2, WP-2.3, WP-2.4

Milestone *Android mobile sensing application*

An application for android mobile devices will be developed for mobile data collection. The application will incorporate smartphone sensors and enable the addition of further

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<sup>2</sup><https://www.ibr.cs.tu-bs.de/projects/inga/>

<sup>3</sup><http://www.ettus.com>

body sensors, for instance, via bluetooth. In addition to the collection of data, the application will enable feedback to the user based on the sensed patterns. For instance, possible feedback would be recommendations conditioned on sensed sentiment. This application will be instrumented in WP-3.2. The purpose of this application is the study of sentiment and the potential of user feedback to alter sentiment related behavior over a longer period of time. In particular, correlations between distinct sensor types, exploited in WP-4, will be utilized to mitigate missing sensor readings (e.g. from medical sensors) with sensor readings from other sensors.

### **WP-3: Experiments**

#### **WP-3.1: Generation of experimental data samples**

Estimated effort 6 PMs

Precondition WP-2

Milestone *Generation of a data set for sentiment analysis*

Utilizing the sentiment sensing system developed in WP-2, we will collect data from medical, smartphone, body and environmental sensors for our sentiment analysis in WP-4. We will consider two classes of medical sensors, for instance, EMG and EOG, acceleration data from the INGA and smartphone sensors as well as RF-signal information captured by USRP devices. We aim at collecting a body of data from 30-50 subjects in laboratory settings in which a series of standard tasks will be conducted by the subjects while the sentiment classes are induced by the experiment design. The subjects will be recruited from students and University staff as well as from patients or medical test persons in cooperation with the medical center at University of Goettingen. At least three sentiment classes will be considered, such as happiness, stress, and tiredness. The experimental setting will be designed to induce these sentiment classes in role-play and interactive games. To generate ground truth, participants we will collect feedback after the experiments. In the test design and execution we will receive support from the Institute of Psychology at TU Braunschweig, let by Professor Simone Kauffeld<sup>4</sup>. The purpose of this workpackage is the generation of data for the development of accurate classifiers for sentiment prediction given all available sensor modalities and the identification of possible correlations between sensor classes.

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<sup>4</sup><https://www.tu-braunschweig.de/psychologie/abt/aos/mitarbeiterinnen/kauffeld/index.html>



### **WP-3.2: Mobile data collection from smartphones**

Estimated effort 6 PMs

Precondition WP-2

Milestone *Generation of a data set for the prediction of sentiment*

We will collect acceleration data from smartphone and body sensors for our sentiment prediction considered in WP-5. In this experiment, the accelerometer data from 10-20 persons will be collected over a period of 6 months both in Israel and Germany. These individuals, recruited from students and staff of both universities, will be equipped with body sensors measuring acceleration data as well as with portable medical sensors. In order to reach dense sampling, we will consider the use of fitness trackers<sup>5</sup> and monetary reward systems. During the experiments, in order to improve our confidence on the ground truth, users will occasionally be asked for feedback by the application. In addition, users will receive recommendations based on the sensed sentiment patterns.

### **WP-3.3: User interaction and feedback**

Estimated effort 3 PMs

Precondition WP-3.2

Milestone *Report on the efficiency of the installed feedback mechanisms*

In this workpackage, the efficiency and performance of the implemented feedback mechanisms of the app implemented in WP-3.2. In particular, this feedback is generated by user questionnaires. In the questionnaire design and execution we will receive support from the Institute of Psychology at TU Braunschweig, led by Professor Simone Kauffeld<sup>6</sup>. Two feedback rounds are implemented in the middle and at the end of WP-3.2 in order to enable adaptation of the feedback in the second phase.

### **WP-4: Sentiment analysis**

#### **WP-4.1: Sentiment analysis from medical sensors**

Estimated effort 3 PMs

Precondition WP-3

Milestone *Suitable features and a classifier for sentiment from at least two types of medical sensors*

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<sup>5</sup>for instance <https://www.fitbit.com/de/chargehr>

<sup>6</sup><https://www.tu-braunschweig.de/psychologie/abt/aos/mitarbeiterinnen/kauffeld/index.html>

In this workpackage we investigate the identification of sentiment from data of medical sensors. We will develop new learning methods for detecting sentiment from EMG and EOG data. These methods will take into consideration the special nature of these signals.

#### **WP-4.2: Sentiment analysis from body and smartphone sensors**

Estimated effort 6 PMs

Precondition WP-3, WP-4.1

Milestone *Correlations between features from medical and smartphone sensors and a classifier for sentiment from these sensors*

We will in this workpackage develop suitable features for the prediction of sentiment from body and smartphone sensors. Our goal is to have a small number of predictive features. In particular, similarly to previous work regarding movement, gestures and pose as indicators of emotion, classifiers for the detection of such classes will be developed and linked to the classification of sentiment. In addition, building on the results from WP-4.1 we will further investigate correlations between sensor readings of medical and acceleration sensors in order to give an estimation to which extent medical sensors can be substituted by cheaper acceleration sensors for the application in large scale on-phone sensing applications.

#### **WP-4.3: Sentiment classification from body and smartphone sensors**

Estimated effort 6 PMs

Precondition WP-3, WP-4.1, WP-4.2

Milestone *Classifier for sentiment over extended period of time*

In this workpackage, we focus the analysis of sentiment over an extended period of time. In particular, we investigate the identification of typical sentiment patterns from the observed sensor data. From this, we focus on the prediction of sentiment based not only on current sensor input, but also on recent historical data. That is, modelling the state-of-mind of a person, and use it to improve prediction of future state-of-mind. In particular, similar to our previous work [46, 45], we consider the use of alignment matching approaches to identify approximately similar sub-patterns in sentiment time series and to predict probable continuation of these patterns.

#### **WP-4.4: Sentiment analysis from environmental sensors**

Estimated effort 6 PMs

Precondition WP-3

Milestone *Features and a classifier for sentiment from received RF-signals*

We will in this workpackage develop features for the prediction of sentiment from received RF signals. Building on our and other previous work detecting movement and gestures from received RF-signals, we will detect gestures, movement and pose of individuals. Then, we will devise new methods to predict from the output of these prediction regarding physical state (movement, gestures and pose) mental state, such as emotion and sentiment.

#### **WP-4.5: Sensor output analysis and fusion**

Estimated effort 3 PMs

Precondition WP-2.1,WP-2.2,WP-2.3

Milestone *Analysis and fusion of output from all sensors.*

In this workpackage we will analyse the sensor data and evaluate their redundancy. This study will be used to develop methods to fuse data from all sensors into a single coherent and compact stream. We will develop methods to remove noise and outliers readings. These tools will be used to process sensor data before feeding it into sentiment prediction models.

#### **WP-5: Prediction of sentiment based on past data and provide feedback for future**

##### **WP-5.1: Integrating past sentiment**

Estimated effort 3 PMs

Precondition WP-3, WP-4

Milestone *A document describing the potential of sentiment analysis of long sensor traces*

We will analyse long sequences of sensor-input and sentimental-state. Our goal is to find long-correlations between the state of the sentiment across in various time scales (minutes, hours, days). Based on these results we will develop models to predict sentiment based on both current sensor data and previous (or historical) sentiment, either predicted (or also given via interface).

## **WP-5.2: Generating user feedback**

Estimated effort 3 PMs

Precondition WP-5-1

Milestone *A document describing the potential of sentiment prediction from long sensor traces*

We will develop few feedback methods to users about current and future predicted sentiment. Our goal is to build an automatic system that will find an optimal feedback mechanism to achieve certain goals, defined by the user. We plan to build on recent advances [73] in multi-armed bandit algorithms based on context which are optimizing exploration of methods and exploiting them.

## **Type and extent of the cooperation and division of tasks between the partners**

Goettingen's expertise lie in mobile pervasive sensing systems, distributed, networked systems and compressive sensing. Technion's expertise lie in the design of new methods for data analysis, building predictive models, and devise highly efficient methods. We envision a relation in which Goettingen take the lead on sensor deployment and analysis, and Technion on analysis and building prediction models. We plan to close the loop, and use the models and analysis-outcome to better improve sensor usage. Smartphones and body sensors will be deployed on both locations. We will to assign a student in each institute, and plan for them to work as a team.

The researchers plan to have periodic phone meetings, and visit each other every six months. We hope that our Goettingen's students will be have long visit in Technion in vice-versa. This will not only advance the project, but will also serve, as a way to deepen their network and the connections between the two institutes.

## **Anticipated results**

This project will generate a body of knowledge on the recognition of sentiment from various sensor types. In particular, in the scope of the project, a prototype implementation for a mobile sentiment recognition app is developed and a corpus of sensor readings together with the associated ground truth is provided. The results will provide insight

into the potential of sentiment sensing and prediction from medical, smartphone and body sensors.

## **Relevant preceding work of the applicants**

### **Prediction of sensor readings**

Stephan Sigg has been working on the prediction/continuation of time series from sensor readings between 2005-2009. In this analytic work he showed that the order in which processing operations are applied to sensor readings impacts the overall error probability for the prediction algorithm, regardless of the actual prediction approach utilized. A stochastic model to estimate this impact has been presented and evaluated in simulations and case studies [45]. Also, a novel class of context-prediction methods based on alignment approaches [46] was derived which was shown to outperform traditional approaches on nominal data sequences. This approach has been re-used by various groups for the prediction of contextual information. Its complexity has been derived analytically and was compared to alternative context prediction methods [45]. The method was applied to readings of inertial sensors, GPS readings and long-time weather data.

### **Recognition of human activities from on-body and RF sensors**

Since 2009 Stephan Sigg considers the use of fluctuations measured on the Radio Frequency (RF) channel for the recognition of activities and gestures. The derived systems exploit multi-path propagation as well as the reflection and blocking of electromagnetic signals. Movement is reflected in the signal strength and fluctuation patterns of a received signal. One benefit of such device-free approaches is that it is not necessary for individuals to actually wear a transmit or receive device. It was shown that the localisation and recognition of simple activities is possible from continuous signals whereas the accuracy is comparable to recognition systems that rely on body-worn accelerometers [47]. These considerations have been extended to passive systems which utilize ambient signals [48]. Recent results show, that it is further possible to detect directed attention from fluctuations on the RF-channel by interpreting body movement captured from RF-readings [43]. Such gestures can be detected based on WiFi RSSI using only time-domain features on an off-the-shelf mobile phone [44].

## **Developing Prediction Models**

Koby Crammer have been working on developing prediction models since his PhD. He developed new methods for assigning one category [66, 65, 68, 67, 64, 84, 93, 92, 94] or more [69, 86] to a given input. The task of predicting sentiment (or composed sentimental state) from sensor input share some properties with these problems. Another related line of research pursued by Koby is predicting sentiment about product from human reviews [82, 81, 75].

Koby also worked extensively on developing new learning methods and models to predict sequential data and taking correlations into account. These methods have been used in text analysis [85, 87], speech analysis [77, 70] and bioinformatics [62, 61, 83].

## **Developing Efficient Algorithms**

Since 2008 Koby have worked largely on new adaptive models and algorithms that are very time and memory efficient. This worked is based on earlier work [71] on online learning. The methods were designed for predicting a real number [74, 89], single bit from an input [75, 72, 76], one out for few [64, 81], or many decisions simultaneously [88, 77]. Additional work pursed are new efficient methods for large scale learning [93, 94].

Koby have also developed new methods that are efficient in interaction with annotation agents, and specifically human annotators. These methods can require annotation only for parts of the input [82, 90, 91], or they actively choose what inputs should be annotated [80, 73, 88].

## **Detecting outliers**

Koby Crammer developed few models to detect outliers in data or finding a small subset of measurements that can be representative and coherent. The methods are either working by enclosing a large subset of inputs in a small ball [78], using non-convex loss functions [63], or rate-distortion methods from information theory [79].

## **Brief details of the type and the extent of previous cooperation between applicants**

The applicants were introduced to each other by a third researcher. They communicated tightly and continuously for both setting the project goal and methods, and, clearly, writ-

ing this application. They plan to collaborate anyway, and this grant will serve as an appropriate platform for a fruitful joint work.

## **Perspectives with respect to possible follow-up projects between the partners with funding from other sources**

Depending on the potential and results of the present project, we are considering to request funding in the frame of the DFG German-Israeli Project Cooperation (DIP)<sup>7</sup> or in the frame of a H2020 FET Open project<sup>8</sup> A further alternative, involving younger scientists, are the establishing of Initial Training Networks<sup>9</sup>.

## **Funding of the project including own contribution**

The project teams consists of the project researchers Dr. Koby Crammer and Dr. Stephan Sigg as well as two PhD students (to be appointed for this project) and assistants.

**UGOE** Dr. Stephan Sigg (externally funded), 3 years

**UGOE** 1 research staff member, TV-L 13, 75% project + 25% external, 3 years

**UGOE** 1 student assistant, 40 hours/week, 3 years

**Technion** Dr. Koby Crammer (externally funded), 3 years

**Technion** 1 research staff member, PhD student for three years

**Technion** 1 postdoctoral fellow, 50% project + 50% externally, 3 years

**Technion** 1 IT engineer, 10% project + 90% externally, 3 years

Technion will make use of the machine learning computing cluster composed of more than 50 nodes. If there will be a need, Technion will make the proper adaptation of the cluster (storage) to the possible requirements of the project. Additionally, some of the funds will be used to purchase the necessary hardware for the project, such as smartphones and USRPs.

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<sup>7</sup>[http://www.dfg.de/en/research\\_funding/programmes/international\\_cooperation/german\\_israeli\\_cooperation/index.html](http://www.dfg.de/en/research_funding/programmes/international_cooperation/german_israeli_cooperation/index.html)

<sup>8</sup><http://ec.europa.eu/programmes/horizon2020/en/h2020-section/fet-open>

<sup>9</sup>[http://ec.europa.eu/research/mariecurieactions/about-mca/actions/itn/index\\_en.htm](http://ec.europa.eu/research/mariecurieactions/about-mca/actions/itn/index_en.htm)

## References

- [1] Bringing gesture recognition to all devices. In *Presented as part of the 11th USENIX Symposium on Networked Systems Design and Implementation*, Berkeley, CA, 2014. USENIX.
- [2] F. Adib, Z. Kabelac, D. Katabi, and R. C. Miller. 3d tracking via body radio reflections. available online: <http://witrack.csail.mit.edu/witrack-paper.pdf>, 2014. Usenix NSDI'14.
- [3] Fadel Adib and Dina Katabi. See through walls with wi-fi. In *ACM SIGCOMM'13*, 2013.
- [4] Matthias Rauterberg Anh-Tuan Nguyen, Wei Chen. The role of human body expression in affect detection: A review. In *10th Asia Pacific Conference on Computer Human Interaction (APCHI 2012)*, 2012.
- [5] Anthony P Atkinson, Mary L Tunstall, and Winand H Dittrich. Evidence for distinct contributions of form and motion information to the recognition of emotions from body gestures. *Cognition*, 104(1):59–72, 2007.
- [6] L. Bao and S. S. Intille. Activity recognition from user-annotated acceleration data. In *Proceedings of PERSASIVE 2004*, volume LNCS 3001, 2004.
- [7] Daniel Bernhardt and Peter Robinson. Detecting affect from non-stylised body motions. In *Affective Computing and Intelligent Interaction*, pages 59–70. Springer, 2007.
- [8] Peter E Bull. *Posture and gesture*. Pergamon press, 1987.
- [9] Rafael A Calvo and Sidney D'Mello. Affect detection: An interdisciplinary review of models, methods, and their applications. *Affective Computing, IEEE Transactions on*, 1(1):18–37, 2010.
- [10] Erik Cambria, Bjorn Schuller, Yunqing Xia, and Catherine Havasi. New avenues in opinion mining and sentiment analysis. *IEEE Intelligent Systems*, page 1, 2013.
- [11] Hong Cao, Minh Nhut Nguyen, Clifton Chun Wei Phua, Shonali Krishnaswamy, and Xiaoli Li. An integrated framework for human activity classification. In *Proceedings of the 14th ACM International Conference on Ubiquitous Computing (UbiComp 2012)*, 2012.
- [12] Ginevra Castellano, Loic Kessous, and George Caridakis. Emotion recognition through multiple modalities: face, body gesture, speech. In *Affect and emotion in human-computer interaction*, pages 92–103. Springer, 2008.
- [13] Ricardo Chavarriaga, Hamidreza Bayati, and Jose del R. Millan. Unsupervised adaptation for acceleration-based activity recognition: robustness to sensor displacement and rotation. *Personal and Ubiquitous Computing*, 2011.



- [14] Gabe Cohn, Dan Morris, Shwetak N. Patel, and Desney S. Tan. Humantenna: Using the body as an antenna for real-time whole-body interaction. In *Proceedings of ACM CHI 2012*, 2012.
- [15] Elizabeth Crane and Melissa Gross. Motion capture and emotion: Affect detection in whole body movement. In *Affective computing and intelligent interaction*, pages 95–101. Springer, 2007.
- [16] Marco De Meijer. The contribution of general features of body movement to the attribution of emotions. *Journal of Nonverbal behavior*, 13(4):247–268, 1989.
- [17] Anind Kumar Dey, K. Wac, D. Ferreira, K. Tassini, J.-H. Hong, and J. Ramos. Getting closer: An empirical investigation of the proximity of user to their smart phones. In *Proceedings of the 13th international conference on Ubiquitous computing*, 2011.
- [18] Allen T Dittmann. The role of body movement in communication. *Nonverbal behavior and communication*, pages 69–95, 1978.
- [19] Sidney D’Mello and Art Graesser. Automatic detection of learner’s affect from gross body language. *Applied Artificial Intelligence*, 23(2):123–150, 2009.
- [20] Paul Ekman and Wallace V Friesen. *Unmasking the face: A guide to recognizing emotions from facial clues*. Ishk, 2003.
- [21] Alois Ferscha, Kashif Zia, and Benedikt Gollan. Collective attention through public displays. In *2012 IEEE Sixth International Conference on Self-Adaptive and Self-Organizing Systems (SASO)*, pages 211 –216, 2012.
- [22] Benedikt Gollan, B. Wally, and Alois Ferscha. Automatic attention estimation in an interactive system based on behaviour analysis. In *Proceedings of the 15th Portuguese Conference on Artificial Intelligence (EPIA2011)*, 2011.
- [23] James J Gross and Ricardo F Muñoz. Emotion regulation and mental health. *Clinical psychology: Science and practice*, 2(2):151–164, 1995.
- [24] Akhil Jaggarwal and Roxanne L Canosa. Emotion recognition using body gesture and pose. Technical report, 2012. available online: [http://www.cs.rit.edu/~axj4159/papers\\_march/report\\_1.pdf](http://www.cs.rit.edu/~axj4159/papers_march/report_1.pdf).
- [25] Patrik N Juslin and Klaus R Scherer. *Vocal expression of affect*. Oxford University Press, 2005.

- [26] Youngwook Kim and Hao Ling. Human activity classification based on micro-doppler signatures using a support vector machine. *IEEE Transactions on Geoscience and Remote Sensing*, 47(5):1328–1337, 2009.
- [27] Adam DI Kramer, Jamie E Guillory, and Jeffrey T Hancock. Experimental evidence of massive-scale emotional contagion through social networks. *Proceedings of the National Academy of Sciences*, page 201320040, 2014.
- [28] Ingrid Lagerlöf and Marie Djerf. Children’s understanding of emotion in dance. *European Journal of Developmental Psychology*, 6(4):409–431, 2009.
- [29] Nicholas D. Lane, Emiliano Miluzzo, Hong Lu, Daniel Peebles, Tanzeem Choudhury, and Andrew T. Campbell. A survey of mobile phone sensing. *IEEE Communications magazine*, 48(9):140–150, September 2010.
- [30] Bing Liu and Lei Zhang. A survey of opinion mining and sentiment analysis. In *Mining text data*, pages 415–463. Springer, 2012.
- [31] Sonia J Lupien, Bruce S McEwen, Megan R Gunnar, and Christine Heim. Effects of stress throughout the lifespan on the brain, behaviour and cognition. *Nature Reviews Neuroscience*, 10(6):434–445, 2009.
- [32] Sonja Lyubomirsky, Laura King, and Ed Diener. The benefits of frequent positive affect: does happiness lead to success? *Psychological bulletin*, 131(6):803, 2005.
- [33] Hanneke KM Meeren, Corné CRJ van Heijnsbergen, and Beatrice de Gelder. Rapid perceptual integration of facial expression and emotional body language. *Proceedings of the National Academy of Sciences of the United States of America*, 102(45):16518–16523, 2005.
- [34] Joann Montepare, Elissa Koff, Deborah Zaitchik, and Marilyn Albert. The use of body movements and gestures as cues to emotions in younger and older adults. *Journal of Nonverbal Behavior*, 23(2):133–152, 1999.
- [35] Selene Mota and Rosalind W Picard. Automated posture analysis for detecting learner’s interest level. In *Computer Vision and Pattern Recognition Workshop, 2003. CVPRW’03. Conference on*, volume 5, pages 49–49. IEEE, 2003.
- [36] Bo Pang and Lillian Lee. Opinion mining and sentiment analysis. *Foundations and trends in information retrieval*, 2(1-2):1–135, 2008.

- [37] Shwetak N. Patel, J. A. Kientz, G. R. Hayes, S. Bhat, and Gregory D. Abowd. Farther than you may think: An empirical investigation of the proximity of users to their mobile phones. In *Proceedings of the 8th international conference on Ubiquitous computing*, pages 123–140, 2006.
- [38] K. Patridge and P. Golle. On using existing time-use study data for ubiquitous computing applications. In *Proceedings of the 10th International Conference on Ubiquitous Computing*, pages 144–153, 2008.
- [39] Thomas Ploetz, Nils Y. Hammerla, Agata Rozga, Andrea Reavis, Nathan Call, and Gregory D. Abowd. Automatic assessment of problem behavior in individuals with developmental disabilities. In *Proceedings of the 14th ACM International Conference on Ubiquitous Computing (Ubicomp 2012)*, 2012.
- [40] Qifan Pu, Sidhant Gupta, Shyam Gollakota, and Shwetak Patel. Whole-home gesture recognition using wireless signals. In *The 19th Annual International Conference on Mobile Computing and Networking (Mobicom'13)*, 2013.
- [41] Nishkam Ravi, Nikhil Dandekar, Preetham Mysore, and Michael L. Littman. Activity recognition from accelerometer data. In *Proceedings of the 17th conference on Innovative applications of artificial intelligence - Volume 3, IAAI'05*, pages 1541–1546, 2005.
- [42] Peter Salovey, Alexander J Rothman, Jerusha B Detweiler, and Wayne T Steward. Emotional states and physical health. *American psychologist*, 55(1):110, 2000.
- [43] Shuyu Shi, Stephan Sigg, Wei Zhao, and Yusheng Ji. Monitoring of attention from ambient fm-radio signals. *IEEE Pervasive Computing, Special Issue - Managing Attention in Pervasive Environments*, Jan-March 2014.
- [44] Stephan Sigg, Ulf Blanke, and Gerhard Troester. The telepathic phone: Frictionless activity recognition from wifi-rssi. In *IEEE International Conference on Pervasive Computing and Communications (PerCom)*, PerCom '14, 2014.
- [45] Stephan Sigg, Dawud Gordon, Georg von Zengen, Michael Beigl, Sandra Haseloff, and Klaus David. Investigation of context prediction accuracy for different context abstraction levels. *IEEE Transactions on Mobile Computing*, 11(6):1047 –1059, june 2012.
- [46] Stephan Sigg, Sandra Haseloff, and Klaus David. An alignment approach for context prediction tasks in ubicomp environments. *IEEE Pervasive Computing*, Oct-Dec 2010, 2010.

- [47] Stephan Sigg, Markus Scholz, Shuyu Shi, Yusheng Ji, and Michael Beigl. Rf-sensing of activities from non-cooperative subjects in device-free recognition systems using ambient and local signals. *IEEE Transactions on Mobile Computing*, 13(4), 2013.
- [48] Stephan Sigg, Shuyu Shi, Felix Buesching, Yusheng Ji, and Lars Wolf. Leveraging rf-channel fluctuation for activity recognition. In *Proceedings of the 11th International Conference on Advances in Mobile Computing and Multimedia (MoMM2013)*, 2013.
- [49] Timothy W Smith, Kelly Glazer, John M Ruiz, and Linda C Gallo. Hostility, anger, aggressiveness, and coronary heart disease: An interpersonal perspective on personality, emotion, and health. *Journal of personality*, 72(6):1217–1270, 2004.
- [50] John F Todaro, Biing-Jiun Shen, Raymond Niaura, Avron Spiro, and Kenneth D Ward. Effect of negative emotions on frequency of coronary heart disease (the normative aging study). *The American journal of cardiology*, 92(8):901–906, 2003.
- [51] CCRJ Van Heijnsbergen, HKM Meeren, J Grezes, and B de Gelder. Rapid detection of fear in body expressions, an erp study. *Brain research*, 1186:233–241, 2007.
- [52] Alexander Varshavsky and Shwetak N. Patel. *Location in Ubiquitous Computing*, pages 285–319. Ubiquitous Computing Fundamentals. Taylor and Francis Group, 2008.
- [53] Harald G Wallbott. Bodily expression of emotion. *European journal of social psychology*, 28(6):879–896, 1998.
- [54] K. Walters and R. Walk. Perception of emotion from body posture. *Bulletin of the Psychonomic Society*, 24(5), 1986.
- [55] C.D. Wickens. *Processing resources in attention*. Academic Press, 1984.
- [56] C.D. Wickens and J.S. McCarley. *Applied attention theory*. CRC Press, 2008.
- [57] F. Wu and B.A. Hubermann. Novelty and collective attention. In *Proceedings of the National Academics of Sciences*, volume 104, pages 17599–17601, 2007.
- [58] Yongchun Xu, Nenad Stojanovic, Ljiljana Stojanovic, and Tobias Schuchert. Efficient human attention detection based on intelligent complex event processing. In *Proceedings of the 6th ACM International Conference on Distributed Event-Based Systems*, DEBS '12, pages 379–380, 2012.
- [59] Tomoko Yonezawa, Hirotake Yamazoe, Akira Utsumi, and Shinji Abe. Gaze-communicative behavior of stuffed-toy robot with joint attention and eye contact based on ambient gaze-tracking. In *ICMI*, pages 140–145, 2007.

- [60] Zhongwu Zhai, Hua Xu, Bada Kang, and Peifa Jia. Exploiting effective features for chinese sentiment classification. *Expert Systems with Applications*, 38(8):9139–9146, 2011.
- [61] Axel Bernal, Koby Crammer, Artemis G. Hatzigeorgiou, and Fernando Pereira. Global discriminative learning for higher-accuracy computational gene prediction. *PLoS Computational Biology*, 3(3), 2007.
- [62] Axel Bernal, Koby Crammer, and Fernando Pereira. Automated gene-model curation using global discriminative learning. *Bioinformatics*, 28(12):1571–1578, 2012.
- [63] K. Crammer and G. Chechik. A needle in a haystack: Local one-class optimization. 2004.
- [64] K. Crammer, M. Dredze, and A. Kulesza. Multi-class confidence weighted algorithms. In *EMNLP*, 2009.
- [65] K. Crammer and Y. Singer. Improved output coding for classification using continuous relaxation. 2000.
- [66] K. Crammer and Y. Singer. On the learnability and design of output codes for multiclass problems. 2000.
- [67] K. Crammer and Y. Singer. On the algorithmic implementation of multiclass kernel-based vector machines. *Journal of Machine Learning Research*, 2:265–292, 2001.
- [68] K. Crammer and Y. Singer. Ultraconservative online algorithms for multiclass problems. 2001.
- [69] K. Crammer and Y. Singer. A new family of online algorithms for category ranking. *Journal of Machine Learning Research*, 3:1025–1058, 2003.
- [70] Koby Crammer. Efficient online learning with individual learning-rates for phoneme sequence recognition. In *Proceedings of the IEEE International Conference on Acoustics, Speech, and Signal Processing, ICASSP 2010, 14-19 March 2010, Sheraton Dallas Hotel, Dallas, Texas, USA*, pages 4878–4881, 2010.
- [71] Koby Crammer, Ofer Dekel, Joseph Keshet, Shai Shalev-Shwartz, and Yoram Singer. Online passive-aggressive algorithms. *Journal of Machine Learning Research*, 7:551–585, 2006.
- [72] Koby Crammer, Mark Dredze, and Fernando Pereira. Confidence-weighted linear classification for text categorization. *J. Mach. Learn. Res.*, 98888:1891–1926, June 2012.
- [73] Koby Crammer and Claudio Gentile. Multiclass classification with bandit feedback using adaptive regularization. *Machine Learning*, 90(3):347–383, 2013.

- [74] Koby Crammer, Alex Kulesza, and Mark Dredze. New  $\mathcal{H}_\infty$  bounds for the recursive least squares algorithm exploiting input structure. In *ICASSP*, pages 2017–2020, 2012.
- [75] Koby Crammer, Alex Kulesza, and Mark Dredze. Adaptive regularization of weight vectors. *Machine Learning*, 91(2):155–187, 2013.
- [76] Koby Crammer and Daniel D. Lee. Learning via gaussian herding. In *Advances in Neural Information Processing Systems 23: 24th Annual Conference on Neural Information Processing Systems 2010. Proceedings of a meeting held 6-9 December 2010, Vancouver, British Columbia, Canada.*, pages 451–459, 2010.
- [77] Koby Crammer and Daniel D. Lee. Online discriminative learning of phoneme recognition via collections of generalized linear models. In *2012 IEEE International Conference on Acoustics, Speech and Signal Processing, ICASSP 2012, Kyoto, Japan, March 25-30, 2012*, pages 1961–1964, 2012.
- [78] Koby Crammer and Yoram Singer. Learning algorithm for enclosing points in bregmanian spheres. In *Computational Learning Theory and Kernel Machines, 16th Annual Conference on Computational Learning Theory and 7th Kernel Workshop, COLT/Kernel 2003, Washington, DC, USA, August 24-27, 2003, Proceedings*, pages 388–402, 2003.
- [79] Koby Crammer, Partha Pratim Talukdar, and Fernando C. Pereira. A rate-distortion one-class model and its applications to clustering. In *Machine Learning, Proceedings of the Twenty-Fifth International Conference (ICML 2008), Helsinki, Finland, June 5-9, 2008*, pages 184–191, 2008.
- [80] Mark Dredze and Koby Crammer. Active learning with confidence. In *Association for Computational Linguistics*, 2008.
- [81] Mark Dredze, Alex Kulesza, and Koby Crammer. Multi-domain learning by confidence-weighted parameter combination. *Machine Learning*, 79(1-2):123–149, 2010.
- [82] Yoav Haimovitch, Koby Crammer, and Shie Mannor. More is better: Large scale partially-supervised sentiment classification. In *Proceedings of the 4th Asian Conference on Machine Learning, ACML 2012, Singapore, Singapore, November 4-6, 2012*, pages 175–190, 2012.
- [83] Qian Liu, Koby Crammer, Fernando C. N. Pereira, and David S. Roos. Reranking candidate gene models with cross-species comparison for improved gene prediction. *BMC Bioinformatics*, 9, 2008.
- [84] Roi Livni, Koby Crammer, and Amir Globerson. A simple geometric interpretation of SVM using stochastic adversaries. In *Proceedings of the Fifteenth International Conference on*

*Artificial Intelligence and Statistics, AISTATS 2012, La Palma, Canary Islands, April 21-23, 2012*, pages 722–730, 2012.

- [85] Ryan McDonald, Koby Crammer, and Fernando Pereira. Large margin online learning algorithms for scalable structured classification. In *NIPS Workshop on Structured Outputs*, 2004.
- [86] Ryan T. McDonald, Koby Crammer, and Fernando Pereira. Flexible text segmentation with structured multilabel classification. In *HLT/EMNLP 2005, Human Language Technology Conference and Conference on Empirical Methods in Natural Language Processing, Proceedings of the Conference, 6-8 October 2005, Vancouver, British Columbia, Canada*, 2005.
- [87] Avihai Mejer and Koby Crammer. Confidence in structured-prediction using confidence-weighted models. In *Proceedings of the 2010 conference on empirical methods in natural language processing*, pages 971–981. Association for Computational Linguistics, 2010.
- [88] Avihai Mejer and Koby Crammer. Training dependency parser using light feedback. In *Proceedings of the 2012 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 488–497. Association for Computational Linguistics, 2012.
- [89] Edward Moroshko and Koby Crammer. Weighted last-step min-max algorithm with improved sub-logarithmic regret. In *ALT*, pages 245–259, 2012.
- [90] Matan Orbach and Koby Crammer. Graph-based transduction with confidence. In *Machine Learning and Knowledge Discovery in Databases - European Conference, ECML PKDD 2012, Bristol, UK, September 24-28, 2012. Proceedings, Part II*, pages 323–338, 2012.
- [91] Matan Orbach and Koby Crammer. Transductive phoneme classification using local scaling and confidence. In *IEEEI*, 2012.
- [92] Ben Zion Vatashsky and Koby Crammer. Multi class learning with individual sparsity. In *IJCAI 2013, Proceedings of the 23rd International Joint Conference on Artificial Intelligence, Beijing, China, August 3-9, 2013*, 2013.
- [93] Zhuang Wang, Koby Crammer, and Slobodan Vucetic. Multi-class pegasos on a budget. In *Proceedings of the 27th International Conference on Machine Learning (ICML-10), June 21-24, 2010, Haifa, Israel*, pages 1143–1150, 2010.

- [94] Zhuang Wang, Koby Crammer, and Slobodan Vucetic. Breaking the curse of kernelization: budgeted stochastic gradient descent for large-scale SVM training. *Journal of Machine Learning Research*, 13:3103–3131, 2012.