Multi-Task Ensemble Learning for Affect Recognition

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CCS CONCEPTS

• Human-centered computing • Human computer interaction (HCI) • Ubiquitous and mobile computing

KEYWORDS

Affective Computing, Human Computer Interaction, Multimodal Sensor Fusion, Deep Neural Networks

1 PROBLEM DOMAIN AND THE SPECIFIC PROBLEM ADDRESSED

Emotions are paramount in the human communication. They serve as a medium to enrich the communication, to express preferences, to communicate subjective cues, and even to manipulate others. The scientific research on emotions has been introduced back in 1868 when Charles Darwin undertook a study to prove that humans have an innate and universal set of emotional expressions. In 1872 the study was published in his book "Expression of the Emotions in Man and Animals" [1]. In 1987, the question "Can computers feel" was raised [2]. In 1997, Picard published her book "Affective Computing" [3], which many consider the start of this scientific field. Two decades afterwards, when Affective Computing is a well-established research field, modeling emotional states still remains a challenging task. Among the main reasons are human subjectivity and inability of artificial intelligent systems to generalize – the lack of general intelligence, where humans excel and AI fails.

Affective states are complex states that results in psychological and physiological changes that influence behaving and thinking [6]. A wearable device equipped with galvanic skin response (GSR – measures sweating rate), Electrocardiography (ECG – measures heart electrical activity) or blood volume pulse (BVP – measures cardiovascular dynamics) sensors can capture these psycho-physiological changes. For example, the affective state of excitement usually initiates changes in heartbeat, breathing, sweating, and muscle tension. These changes can be captured via physiological sensors. Based on the data from the physiological sensors, machine learning (ML) models for affect recognition can be built.

The two specific problems that our work addresses are method quality (affect recognition accuracy) and method generality (the ability to work on diverse datasets).

Method quality: The straightforward approach for improving the method quality is to collect larger datasets and use ML algorithms with large learning capacity, such as the deep learning architectures. However, collecting a large dataset in affective computing is time consuming and expensive. Instead of collecting one single dataset, one can combine datasets from several affect recognition domains that are collected with similar physiological sensors, and then learn a unified deep multimodal affect recognition model. To successfully combine several datasets, we are proposing a robust preprocessing method that removes the hardware and person-specific issues. After preprocessing, the data that comes from same type of sensors (e.g., two different ECG sensors) should be similar regardless of the hardware. In addition, not all databases are collected using the same number of sensors. For that reason, we are proposing learning ensembles of ML models, where each model targets a specific sensor combination.

Method generality: There are dozens of computer science studies in which affect recognition has been addressed, and in most of the studies, only one domain (dataset) is targeted, e.g., emotion recognition while watching videos or listening to music, stress monitoring while solving mathematical tasks, cognitive load monitoring while driving a car and similar. However, a model that is built and tuned only on one dataset, one environment and one type of hardware, would be destined to failure on another domain. In different situations different people react differently. Added to that is the specific noise that each hardware produces, making it is nearly impossible to use a computer model trained in one environment on another environment, unless all these factors have been addressed. Our approach for improving the method generality for affect recognition is based on learning from semantically similar, yet technically quite heterogeneous data from physiological sensors. The ML subfield capable of learning models for several tasks in parallel while using a shared representation is Multi-task learning (MTL) [4]. The motivation is to use what was learned for each task to help other tasks be learned better. By utilizing MTL approach we are developing ensembles of MTL models on several affective datasets from varying environments (e.g., while driving, while watching multimedia, while working, and similar), recorded with varying

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hardware and varying sensor placements (e.g., chest-worn Electrocardiography – ECG sensors, finger-worn blood volume pulse - BVP sensors, wrist-worn pulse oximeter – PPG sensor, chest-worn and wrist-worn GSR sensor, and similar). The idea is that the more environments and the more data from different sensors the models observe, the more general knowledge they can learn. If the method developed will be able to successfully generalize the semantical concepts of emotions from heterogeneous data, it will also enable another insight into creating general intelligence.

2 OVERVIEW OF RELATED WORK IN THE AREA OF THE PHD WORK

Affect recognition is an established computer-science field, but one with many challenges remaining. There has been many studies confirming that affect recognition can be performed using speech analysis [12], video analysis [13], or physiological sensors in combination with ML. The majority of the methods that use physiological signals use data from ECG, electroencephalogram (EEG), functional magnetic resonance imaging (fMRI), galvanic skin response (GSR), electrooculography (EOG) and/or BVP sensors. In general, the methods based on EEG data outperform the methods based on other data [7] [8], probably because the EEG provides a more direct channel to one's mind.

2.1 Standard Machine learning for affect recognition

Regarding the typical ML approaches for affect recognition, Iacoviello et al. have combined discrete wavelet transformation, principal component analysis and support vector machine (SVM) to build a hybrid classification framework using EEG [16]. Khezri et al. used EEG combined with GSR to recognize six basic emotions via K-nearest neighbors (KNN) classifiers [17]. Verma et al. [18] developed an ensemble approach using EEG, electromyography (EMG), ECG, GSR, and EOG. Mehmood and Lee used independent component analysis to extract emotional indicators from EEG, EMG, GSR and ECG [19]. Mikuckas et al. [20] presented a HCI system for emotional state recognition that uses spectro-temporal analysis only on R-R signals. More specifically, they focused on recognizing stressful states by means of heart rate variability (HRV) analysis.

2.2 Deep learning for affect recognition

Recently, the use of deep learning for affect recognition became popular. Liu et al. [21] presented a deep learning approach for emotion recognition using EEG data and eye blink data. They experimented on two different datasets, DEAP and SEED dataset [22]. Similarly, Bashivan et al. [23] presented an approach for learning representations from EEG signal with deep recurrent-convolutional neural networks. Yin et al. presented an approach for the recognition of emotions using multimodal physiological signals and an ensemble deep learning model using EEG, EMG, ECG, GSR, EOG, BVP, respiration rate and skin temperature [24]. In contrast to the EEG-based methods for affect recognition, Martinez et al. [25] presented a DNN method for affect recognition from GSR and BVP data.

2.3 Multi-task learning for affect recognition

Xia, and Liu proposed an MTL framework for recognizing continuous and discrete emotions from speech as two separate tasks [27]. Taylor et al. [26] used MTL for building personalized models for predicting mood, stress, and health using data collected from surveys, wearable sensors, smartphone logs, and the weather. Similarly, Lopez-Martinez and Picard presented an MTL approach building personalized models for pain recognition [31]. All of these studies focused on data collected in one study.

2.4 Related work summary

The related work shows that most of the research is performed on the same or similar-type domains. In addition, it was demonstrated that deep learning can outperform classical ML in affect recognition and the MTL techniques can bring an additional improvement.

We plan to build upon the state-of-the-art studies by creating ensembles of MTL models for affect recognition. Instead of focusing on one dataset, one environment and one type of sensors, we will use heterogeneous data for the input. Instead of focusing a single task, we will create general and transferable affect recognition models that will provide "warm start" for building new ML models in new, affective computing domains.

3 METHODOLOGICAL APPROACH CHOSEN

The proposed method is presented in Figure 1. The method consists of four main components: labelled datasets for affect recognition, a preprocessing component, an MTL component and task-specific ensembles. Each component is described in the following subsections.

3.1 Labelled datasets

Instead of collecting a large dataset for affect recognition, we propose combining datasets from several heterogeneous affect recognition domains that are collected with similar physiological sensors.

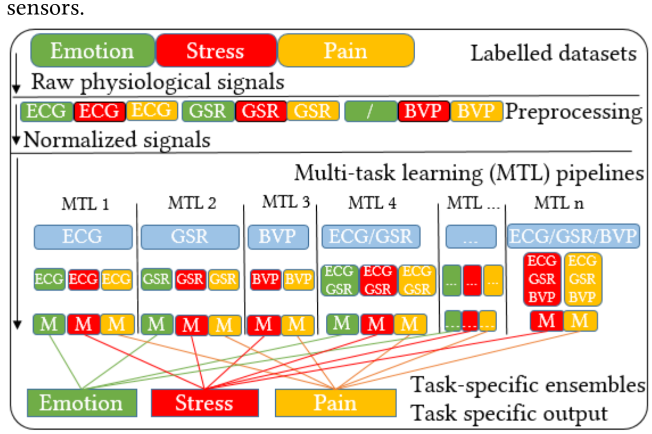

Figure 1. Proposed Multi-Task Ensemble Learning for Affect Recognition

In the presented example in Figure 1, the Emotion dataset (green) contains data from ECG and GSR sensor, and the other two datasets (red and yellow) contain data form ECG, GSR and BVP sensors.

3.2 Preprocessing components

A prerequisite for learning general models from several datasets is a robust preprocessing method used for translating the physiological datasets into a common representation. For example, some GSR sensors measure skin conductivity and others measure skin resistivity. Some people sweat more in general, and some less. Some ECG sensors remove the mean drift in the data and some do not. In its essence, the normalization step removes the hardware and person-specific noise. Depending on the sensors, we will experiment with frequency-based filters (e.g., band pass, Butterwoth, Checyshev, Elliptic, etc.), time-based filters (e.g., rolling mean filters) and finally we will experiment with person-specific normalizations, i.e., min-max normalization, standardization and similar. For each sensor type we will determine the combination of filters that most successfully unifies the data. In some cases, we may not be able to determine a combination of filtering steps that would provide a common output for different hardware. In this cases, we will try normalization in the feature space. For example, in our previous study we analyzed ECG data form four different sensors, and instead of normalizing the raw ECG data, we first extracted the R-R intervals form each sensors, and then we performed person-specific normalization of the R-R intervals.

3.3 Multi-task learning component

In single-task neural networks, backpropagation algorithm is used to minimize a single loss function (e.g., binary cross-entropy) [31]. MTL, on the other hand, involves the simultaneous training of two or more related tasks over shared representations (see Figure 2).

The MTL component in Figure 1 utilizes several MTL pipelines. Each MTL pipeline is dedicated to one sensor combination (i.e., one type of input) and simultaneously builds dataset-specific models for the specific sensor combination. Our ambition is to learn general knowledge about the related tasks through the shared representations (general intelligence; g factor). The size of the shared layers can vary in width and depth. For example, there can be several convolutional layers, used to automatically extract features form the sensor specific data, and the output of the convolutional layers can be fed to task-specific fully-connected layers to learn the dataset-specific models.

The number of dataset-specific models in each MTL pipeline corresponds to the number of labelled datasets containing the specific combination. For example, the green dataset (Emotion) does not contain data from BVP sensor, thus the BVP pipeline contains only red and yellow models, i.e., models for Stress and Pain recognition. The number of MTL pipelines (presented as vertical pipelines in the Figure 1) corresponds to the maximum number of sensor combinations available in the datasets.

3.4 Task-specific ensembles

For each possible sensor combination in each dataset (task), the MTL component creates separate task-specific models through the MTL pipelines. Thus, if one dataset contains two sensors, the MTL component would learn three different models for the specific task, while for three sensors it would learn seven different models, and so on. However, when a new instance comes for a specific task, we would like to output only one prediction. For that reason, a task-specific meta model is learned. The task-specific meta model receives as input the output predictions of each MTL model for the specific task (MTL task-specific models) and outputs the final prediction. The task-specific meta model and the MTL task-specific models constitute the task-specific ensembles.

4 ORIGINAL KEY IDEA AND CORRESPONDING HYPOTHESIS OF THE THESIS

The key idea in the presented paper is the combining datasets from several affect recognition domains that are collected with similar physiological sensors and then learning a unified deep multimodal affect recognition model that would outperform dataset-specific models.

We propose the following goals that lead toward the implementation of the key idea:

(1) Implementation of a dataset normalization technique for merging similar datasets with similar sensors in the affective computing domains. The normalization would allow for building more complex, more general and transferable affect recognition models.

(2) Multi-Task Ensemble Learning with input from normalized, semantically similar, yet technically quite heterogeneous data from physiological sensors that will lead to learning multiple shared representations which will contain general affect recognition knowledge. The general affect recognition knowledge will improve the performance of the affect recognition systems over the traditional single-task approaches for affect recognition.

Working hypothesis: Combining datasets from several affect recognition domains that are collected with similar physiological sensors, and then learning MTL ensembles for affect recognition through generalization, will outperform single-task models for affect recognition including: (1) baseline ML models - built with standard ML algorithms (e.g., Random Forest, SVM and similar) and hand-crafted features; (2) sophisticated deep learning models – built with raw signals; and hand-crafted features.

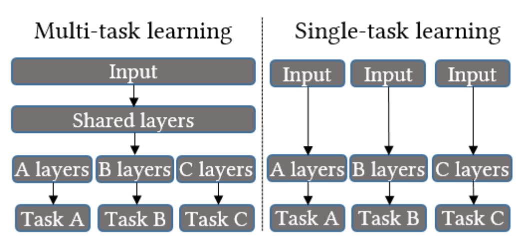

Figure 2. Multi-task vs Single-task learning

5 RESEARCH CARRIED OUT SO FAR AND PLANNED AHEAD

5.1 Research carried out so far

We managed to record two datasets for affect recognition, one for monitoring stress level while solving mathematical equations [30], and one for monitoring cognitive load while solving psychological tests. In addition, we accessed five publically available datasets for emotion recognition from physiological signals (Ascertain [7], Deap [8], Mahnob [33], Amigos [34], Decaf_Music and Decaf_Video [35], and one dataset for monitoring drivers' workload [29]. Thus, our method has access to eight different datasets for affect recognition.

The basis of the MTL pipelines are deep learning models capable of taking as input different type sensors data. In our recent study, we analyzed datasets for affect recognition from physiological signals and proposed a method capable of combining them. The novel method is compared to classical ML. For both methods, the raw data from GSR, ECG, and BVP sensors is processed and transformed into a common spectro-temporal space of R-R intervals and GSR data by utilizing the preprocessing component. For the classical ML algorithms, features are extracted, and for the DNN algorithms, two different approaches were taken: a fully connected DNN (DNN-Feat) trained with the same features as the classical ML algorithms and a Convolutional Neural Network (CNN-GSR) trained with the temporal representation of the GSR signal. Finally, a fully connected DNN meta learner is trained to utilize the knowledge from the two different DNNs and to tune the DNN models for the target dataset.

The results are presented in Table 1. The fist column presents the ML algorithm. The column Merged shows the accuracy of the algorithms when they are trained on the overall (merged) data. The other columns represent the accuracy of dataset-specific models. From Table 1 it can be seen that the DNN ensemble method has achieved average accuracy of 70%, which is four percentage points better than the other DNN-based methods and at least seven percentage points better than the non-DNN methods. Regarding the results per dataset, on the Mahnob dataset, the DNN-ensemble method has achieved accuracy of twenty percentage points more than other methods. On the Amigos dataset, DNN-ensemble method has achieved accuracy of ten percentage points more than other methods. On the other four datasets, the DNN-ensemble method has achieved similar results as the rest of the methods. The full study will be presented at the 2nd IJCAI workshop on Artificial Intelligence in Affective Computing[3].

5.2 Research planned

Our work on arousal recognition using ensembles of DNN networks is a base for the development of the proposed Multi-Task ensembles. The next septs are:

(1) Our previous work was focused only on one task - Arousal recognition from physiological signals. Next, we plan to include other tasks in affective computing, including: valence recognition, emotion recognition, stress recognition, cognitive load recognition and similar.
(2) In the previous work, we experimented with ECG, BVP and GSR signals. Next, we plan to include other physiological sensors utilized in affect recognition studies (e.g., EEG, breathing rate, skin temperature, EMG sensor and similar).
(3) We will develop a novel deep learning architecture (as depicted in Figure 1) that will be more general compared to our previous work. The generalization will allow for simultaneous learning from several affect recognition datasets and will bring additional improvement over single-dataset architectures.
(4) Finally, the models learned with the deep learning architecture will be evaluated on new, unseen affective computing domain(s).

Our ultimate goal is to bring the Affective Computing research one step closer to the general (affective) intelligence. Namely, the proposed MTL ensemble learning approach will develop a general model that will contain knowledge form many different domains in Affective Computing. For a new domain, that has not been included in the overall training data, but contains some of the modalities (sensors), one can simply use transfer-learning methods to adapt the model for the specific needs. For example, one can calculate the outputs of the different MTL pipelines or even the outputs from the different neural network layers in the MTL pipelines. These outputs can serve as abstract features, which will be input to any other ML algorithm. This mechanism allows for transfer of knowledge from the general domain to a specific domain. Transfer of knowledge from one domain to another domain is very natural for the human brain, and hopefully, this research will bring the computers one-step closer to that ability.

6 EVALUATION METHODS

6.1 Dataset collection

All affect recognition methods are evaluated using labelled datasets collected in affective computing studies. Besides the existing datasets for affect recognition, which we are already analyzing (see Table 1), we recorded two additional datasets for affect recognition, one for monitoring stress level while solving mathematical equations [30], and one for monitoring cognitive load while solving psychological tests. A paper describing this dataset has been submitted to the UbiComp's workshop on Smart & Ambient Notification and Attention Management. Both datasets contain data for 23 subjects monitored with a wrist-device equipped with physiological sensors. In both datasets, the ground truth is labelled by using subjective psychological questionnaires relevant for the specific task.

[3] http://kdd.cs.ksu.edu/Workshops/IJCAI-2018-AffComp/

Table 1. Accuracy for binary arousal recognition (high vs. low) for six datasets.

Algorithm	Merged	Ascertain	DEAP	Driving	Cog. Load	Mahnob	Amigos
RF	59.3	65.5	55.6	78.5	73.9	58.0	53.6
SVM	60.2	66.4	51.3	79.5	69.1	62.3	50.6
GB	59.0	64.4	53.3	75.5	76.1	60.9	54.2
AdaB	57.5	62.3	52.6	75.5	76.6	61.0	56.0
KNN	60.6	60.0	49.0	75.0	77.0	60.1	53.3
NB	60.8	59.1	53.5	66.5	80.4	62.4	45.4
DT	58.0	65.0	52.0	61.5	70.4	58.1	55.1
ML-Meta	63.0	59.0	52.5	74.4	76.3	61.8	53.8
DNN-Feat	66.2						
CNN-GSR	66.3						
DNN-Ens	70.3	64.10	52.05	78.67	76.12	83.98	66.62

6.2 Comparison with existing approaches for affect recognition

We will compare the proposed Multi-Task Ensemble Learning with other single-task ML algorithms for affect recognition including baseline ML models - built with standard ML algorithms (e.g., Random Forest, SVM and similar); and sophisticated deep learning models – built with raw signals; and hand-crafted features. The hand-crafted features include time-based and frequency-based features from the physiological signals including Heart Rate Variability (HRV) analysis which is widely used for stress and emotion recognition [36].

6.3 Evaluation metrics

We will use typical evaluation metrics for ML algorithms including accuracy, precision and recall. These metrics will show the performance of the ML methods on the test datasets. In addition, we will follow different evaluation protocols: (1) Leve-one-dataset-out, which will present the methods performance on a new, unseen dataset. (2) Leave-one-person-out, which will present the methods performance on a new, unseen person. (3) Leave-one-trial-out, which will present the methods performance in situation where we can afford one person's data in the learning and in the testing phase.

7 CONTRIBUTION IN THE FIELD OF UBIQUITOUS COMPUTING

The expected contributions to the field of ubiquitous computing are as follows:

- New labelled datasets for affect recognition from wearable physiological signals. The two datasets contain data of 23 subjects (per dataset). At least one of the datasets will be publically available for research purposes.
- Dataset normalization techniques for merging similar datasets in the affective computing domains. The normalization would allow for building more complex, more general and transferable affect recognition models and would provide "warm start" for building new ML models in new, similar affective computing domain.
- Contributions to affective computing community via novel algorithm (presented in Figure 1) that will be able to learn from large amount of raw physiological data. The propose algorithm is general enough to be used for similar problems in affective computing.
- Possible societal impact through better understanding of human affective states from physiological sensors which may be applied in the domain of human-computer interaction, the healthcare domain, the automotive industry and similar domains which can benefit from affect-aware systems.

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