Survey Paper on Personalized Multitask Learning for Predicting Stress and Mood

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Abstract - *The idea of estimating mood, stress, and mental health indicators using unobtrusive data collected from smartphones and wearables has been garnering increasing interest. Detecting workplace stress is another growing body of research. A detailed study reported that an omnibus model trained to detect all people's mood based on smartphone communication and usage resulted in a prediction accuracy of 66 percent. However, if two months of labeled data were collected for each person, then individual, independent personalized models could be trained to achieve 93 percent accuracy in mood classification. Since obtaining two months of training data per person can be considered somewhat unrealistic, the researchers investigated methods for training a hybrid model that weights personalized examples more heavily, which can be used when there are fewer labeled training examples per person. While accurately predicting mood and wellbeing could have a number of important clinical benefifits, traditional machine learning (ML) methods frequently yield low performance in this domain. This is because a one-size-fits-all machine learning model is inherently ill-suited to predicting outcomes like mood and stress, which vary greatly due to individual differences. Therefore, by employ Multitask Learning (MTL) techniques to train personalized ML models which are customized to the needs of each individual, but still leverage data from across the population. MTL account for individual differences provides large performance improvements over traditional machine learning methods and provides personalized, actionable insights. To increase the accuracy, can make use of several features as important for mental health and wellbeing for improving MTL.*

***Key Words*: Machine learning, Multitask Learning, Mood prediction.**

1. INTRODUCTION

Perceived wellbeing, as measured by self-reported health, stress, and happiness, has a number of important clinical health consequences. Stress increases susceptibility to infection and illness. Self-reported health is so strongly related to actual health and all-cause mortality, that in a 29-yearstudy it was found to be the single most predictive measure of mortality, above even more objective health measures such as blood pressure readings. Clearly, the ability to model and predict subjective mood and wellbeing could be immensely beneficial, especially if such predictions could be made using data collected in an unobtrusive and privacy-sensitive way, perhaps using wearable sensors and smartphones. Such a model could open up a range of beneficial applications which passively monitor users' data and make predictions about their mental and physical wellbeing. The predictions could be useful to any person who might want a forecast of their future mood, stress, or health in order to make adjustments to their routine to attempt to improve it. For example, if the model predicts that I will be extremely stressed tomorrow, I might want to choose a different day to agree to review that extra paper[1]. Unfortunately, modeling wellbeing and mood is an incredibly difficult task, and a highly accurate, robust system has yet to be developed. Most of the models suffer from a common problem: the inability to account for individual differences. What puts one person in a good mood does not apply to everyone else. For instance, the stress reaction experienced by an introvert during a loud, crowded party might be very different for an extrovert. Individual differences in personality can strongly affect mood and vulnerability to mental health issues such as depression. There are even individual differences in how people's moods are affected by the weather. Thus, a generic, omnibus machine learning model trained to predict mood is inherently limited in the performance it can obtain.

Accounting for interindividual variability via MTL can dramatically improve the prediction of these wellbeing states: mood, stress, and health. MTL is a type of transfer learning, in which models are learned simultaneously for several related tasks, but share information through similarity constraints.

MTL can allow each person to have a model tailored specifically for them, which still learns from all available data. Therefore, the approach remains feasible even if there is insufficient data to train an individual machine learning model for each person. By adapting existing MTL methods to account for individual differences in the relationship between behavior and wellbeing. In addition to showing the benefits of personalization, a more challenging task is undertaken typically attempted when modeling mood. While most prior work has focused on detecting current mood state, here the ability to predict mood and wellbeing tomorrow night (at least 20 hours in the future), using only data from today is tested[1]. Specifically, assume x_t represents all the smartphone, wearable sensor, and weather data collected about a person on day t (from 12:00 am to 11:59 pm). Let y_t be the person's selfreported mood, stress, and health in the evening of day t (reported after 8 pm). Most of the previous works has focused on learning to model $p(y_t/x_t)$; that is, the probability of the person's current mood given the current data, which refer to as mood detection. In contrast, learn $p(y_{t+1}/x_t)$, the probability of the person's mood tomorrow given today's data. This type of prediction could be considered a type of mood forecasting, providing an estimate of a person's future wellbeing which could potentially allow them to better prepare for it. Learning $p(y_{t+1}/x_t)$, allowing us to predict an individual's mood without ever requiring them to manually input a mood rating. This work predict future wellbeing without requiring a history of collected wellbeing labels for each person[1]. Because the data are gathered in the "wild" as participants go about their daily lives, using surveys, wearable sensors, weather monitoring, and smartphones, and thus are relevant to use in a real-world wellbeing prediction system.

2. LITERATURE REVIEW

Sara Taylor et.al.[1] proposed Personalized Multitask Learning for Predicting Tomorrow's Mood, Stress, and Health. Employed Multitask Learning (MTL) techniques to train personalized ML models which are customized to the needs of each individual, but still leverage data from across the population. Three formulations of MTL are compared: i) MTL deep neural networks, which share several hidden layers but have final layers unique to each task; ii) Multi-task Multi-Kernel learning, which feeds information across tasks through kernel weights on feature types; and iii) a Hierarchical Bayesian model in which tasks share a common Dirichlet Process prior. These techniques are investigated in the context of predicting future mood, stress, and health using data collected from surveys, wearable sensors, smartphone logs, and the weather. Empirical results demonstrate that using MTL to account for individual differences provides large performance improvements over traditional machine learning methods and provides personalized, actionable insights.

Ahmad Rauf Subhani et.al.[2] proposed Machine Learning Framework for the Detection of Mental Stress at Multiple Levels. Stress is commonly recognized as a state in which an individual is expected to perform too much under sheer pressure and in which he/she can only marginally contend with the demands. Mental stress has become a social issue and could become a cause of functional disability during routine work. Stress increases the likelihood of depression, stroke, heart attack, and cardiac arrest. In this paper, a machine learning (ML) framework involving electroencephalogram (EEG) signal analysis of stressed participants is proposed. The proposed ML framework involved EEG feature extraction, feature selection (receiver operating characteristic curve, t-test and the Bhattacharya distance), classification (logistic regression, support vector machine and naive Bayes classifiers) and tenfold cross validation.

Natasha Jaques et.al.[3] proposed Multi-task, Multi-Kernel Learning for Estimating Individual Wellbeing. Depression is a widespread and serious problem, disproportionately affecting college-aged individuals. The ability to handle negative life events without becoming depressed, termed resilience, depends on several factors related to overall wellbeing; these include social support, engagement with work, happiness , physical health, and sleep. For this they made use of a dataset SNAPSHOT: Sleep, Networks, Affect, Performance, Stress, and Health using Objective Techniques. Multi-task Multi-Kernel Learning (MTMKL) is applied to the problem of modeling students' wellbeing. Because wellbeing is a complex internal state consisting of several related dimensions, Multi-task learning can be used to classify them simultaneously. Multiple Kernel Learning is used to efficiently combine data from multiple modalities.

Rui Xia et. al.[4] proposed A Multi-Task Learning Framework for Emotion Recognition Using 2D Continuous Space. In this study, focus is on speech based emotion recognition. In this work, they propose multi-task learning to leverage activation and valence information for acoustic emotion recognition based on the deep belief network (DBN) framework. Categorical emotion recognition task is treated as the major task. For the secondary task, leverage activation and valence labels in two different ways, category level based classification and continuous level based regression. The combination of the loss functions from the major and secondary tasks is used as the objective function in the multi-task learning framework. The DBN is trained to simultaneously optimize the classification performance for the major emotion classification task and this secondary task. The DBN system is learned to lower the regression error of the secondary task while minimizing the classification error of the major task.

Saskia Koldijk et.al.[5] proposed Detecting Work Stress in Offices by Combining Unobtrusive Sensors. The focus of this paper is on developing automatic classifiers to infer working conditions and stress related mental states from a multimodal set of sensor data (computer logging, facial expressions, posture and physiology). This paper address two methodological and applied machine learning challenges: One is Detecting work stress using several (physically) unobtrusive sensors, and second Taking into account individual differences. A comparison of several classification approaches showed that, for SWELL-KW dataset, neutral and stressful working conditions can be distinguished with 90 percent accuracy by means of SVM. Posture yields most valuable information, followed by facial expressions. Furthermore, it found that the subjective variable 'mental effort' can be better predicted from sensor data than, e.g., 'perceived stress'.

Yu Zhu et.al.[6] proposed Automated Depression Diagnosis Based on Deep Networks to Encode Facial Appearance and Dynamics. In this paper, the study focus on the problem of automatic diagnosis of depression. A new approach to predict the Beck Depression Inventory II (BDI-II) values from video data is proposed based on the deep networks. The proposed framework is designed in a two stream manner, aiming at capturing both the facial appearance and dynamics. By employ joint tuning layers that can implicitly integrate the appearance and dynamic information. Experiments are conducted on two depression databases, AVEC2013 and AVEC2014. This paper studies depression recognition and propose a new approach to model the facial appearance and dynamics, based on deep convolutional neutral networks (DCNN). The approach is designed in a two-stream manner, combined with joint-tuning layers for depression prediction. Specifically, facial appearance representation is modeled through a very deep neural network, using face frames as the input. Facial dynamics are modeled by another deep neural network, with face "flow images" as the input. Face "flow images" are generated by computing within the video sub-volumes using the optical flow, to capture facial motions. The two deep networks are then integrated by joint-tuning layers into one deep network, which can further improve the overall performance.

Pouneh Soleimaninejadian et.al.[7] proposed Mood Detection and Prediction Based on User Daily Activities. Studies show that mood states influence our daily life quality and activities, and this is not the only way around. Mood also changes because of how we spend our days.In this study data on users' daily lives (known as lifelog) to both detect and predict their mood is used. The states of mood in this paper are based on Thayer's two-dimensional model of mood. This is the first research to analyze in depth the physical data collected in lifelog and its link to determinants and effects of mood including biometrics, physical activities, sleep quality, diet and user's environment.

Han Yu et.al.[8] proposed Personalized Wellbeing Prediction using Behavioral, Physiological and Weather Data. The work built and compared several machine learning models to predict future self-reported wellbeing labels (of mood, health, and stress) for next day and for up to 7 days in the future, using multi-modal data. The data are from surveys, wearables, mobile phones and weather information collected in a study from college students, each providing daily data for 30 or 90 days and compared the performance of multiple models, including personalized multi-task models and deep learning models.

S. Dhananjay Kumar et.al.[9] proposed Prediction of Depression from EEG Signal using Long Short Term Memory(LSTM). Depression, a neurological disorder is the leading cause of disability worldwide. EEG recordings have found wide use in the diagnosis and analysis of various neurological disorders including depression. In this paper, LSTM (Long-short term memory) deep learning models are used in the prediction of trends of depression for the next time instants, based on the features extracted. The statistical time-domain feature encompassing the mean of amplitude of the data is extracted employing moving window segmentation from the acquired EEG signals. The model uses one LSTM layer with 10 hidden neurons for the prediction. Out of a total of 7000 mean values calculated from a sample of 30 patient records from each resting states, 5600 sample means were used to train the model. The proposed LSTM network could predict the next 1400 sample mean values accurately with root mean square error of 0.000064.

Sadari Jayawardena et.al.[10] proposed Support Vector Ordinal Regression for Depression Severity Prediction. There has been significant research in automatic depression prediction in recent years due to deficiencies in current diagnostic methods. Thus far, depression severity is predicted either as a classification or regression task ignoring the ordinality of depression scores. This paper highlights the importance of using ordinal regression algorithms for ordinal response data by comparing with multiclass classification and regression using support vector framework. This study has compared ordinal regression (RankSVM) with multiclass classification and regression for depression score prediction using two synthetic datasets and the DAICWOZ depressed speech database.

Ji-won Baek et. al.[11] proposed Context Deep Neural Network Model for Predicting Depression Risk Using Multiple Regression. This study proposes the context-DNN model for predicting depression risk using multiple-regression. The context of the proposed context DNN consists of the information to predict situations and environments influencing depression in consideration of context information. Each context information related to predictor variables of depression becomes an input of DNN, and variable for depression prediction becomes an output of DNN. For DNN connection, the regression analysis to predict the risk of depression is used so as to predict the potential context influencing the risk of depression. According to the performance evaluation, the proposed model was evaluated to have the best performance in regression analysis and comparative analysis with DNN.

Walter Gerych et.al.[12] proposed Classifying Depression in Imbalanced Datasets using an Autoencoder-Based Anomaly Detection Approach. Untreated depression can significantly decrease quality of life, physical health, and has significant economic and societal costs. The traditional method of diagnosing depression requires the patient to respond to medical questionnaires and is subjective. In this work, anomaly detection methods as a method for mitigating class imbalance for depression detection is explored. The approach adopts a multi-stage machine learning pipeline. First, using autoencoders, project the mobility features of the majority class (undepressed users). Thereafter, the trained autoencoder then classifies a test set of users as either depressed (anomalous) or not depressed (inliers) using a One Class SVM algorithm. The method, when applied to the real-world StudentLife data set shows that even with an extremely imbalanced dataset, this method is able to detect individuals with depression symptoms with an AUC-ROC of 0.92, significantly outperforming traditional machine learning classification approaches.

Natasha Jaques et.al.[13] proposed Predicting students' happiness from physiology, phone, mobility, and behavioral data. In order to model students' happiness, applied machine learning methods to data collected from undergrad students monitored over the course of one month each. The data collected include physiological signals, location, smartphone logs, and survey responses to behavioral questions. Each day, participants reported their wellbeing on measures including stress, health, and happiness. Because of the relationship between happiness and depression, modeling happiness may help us to detect individuals who are at risk of depression and guide interventions to help them. This work is also interested in how behavioral factors (such as sleep and social activity) affect happiness positively and negatively. A variety of machine learning and feature selection techniques are compared, including Gaussian Mixture Models and ensemble classification. Almost 70% classification accuracy of self-reported happiness on held-out test data is achieved.

3. CONCLUSION

MTL is a type of transfer learning, in which models are learned simultaneously for several tasks but share information through similarity constraints. MTL can be used across a variety of models. It can be considered a form of regularization, and can improve generalization performance as long as tasks are sufficiently related. Because MTL is beneficial when training data is scarce and noisy, it is well-suited to the messy, real-world problem of predicting mood. MTL can substantially improve mood and wellbeing prediction performance. This performance enhancement is not simply due to the application of MTL, but rather through the ability of MTL to allow each person to have a model customized for them, but still benefit from the data of other people through hidden layers of a deep neural network, kernel weights, or a shared prior.

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