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PREDICTING THE INDIVIDUAL MOOD LEVEL BASED ON DIARY DATA

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PREDICTING THE INDIVIDUAL MOOD LEVEL BASED ON DIARY DATA

Research Paper

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Abstract

Understanding mood changes of individuals with depressive disorders is crucial in order to guide personalized therapeutic interventions. Based on diary data, in which clients of an online depression treatment report their activities as free text, we categorize these activities and predict the mood level of clients. We apply a bag-of-words text-mining approach for activity categorization and explore recurrent neuronal networks to support this task. Using the identified activities, we develop partial ordered logit models with varying levels of heterogeneity among clients to predict their mood. We estimate the parameters of these models by employing Markov Chain Monte Carlo techniques and compare the models regarding their predictive performance. Therefore, by combining text-mining and Bayesian estimation techniques, we apply a two-stage analysis approach in order to reveal relationships between various activity categories and the individual mood level. Our findings indicate that the mood level is influenced negatively when participants report about sickness or rumination. Social activities have a positive influence on the mood. By understanding the influences of daily activities on the individual mood level, we hope to improve the efficacy of online behavior therapy, provide support in the context of clinical decision-making, and contribute to the development of personalized interventions.

Keywords: Decision Support, E-Mental-Health, Text-Mining, Bayesian Method, Personalized Treatments

1 Introduction

A good state of mental health is crucial for every individual as it provides general motivation in achieving life goals and a healthy environment. However, many individuals lack proper mental health and suffer from a variety of mental health disorders. Studies report a striking 7% of the European society as having suffered from major depression (Wittchen et al., 2011). Depression, being just one out of hundreds of various types of mental disorders, creates a mental, social, emotional, and financial burden that not just affects the 7% of individuals diagnosed, but also the families of those individuals while at the same time even imposing financial expenses at the government level (Gustavsson et al., 2011; Leger, 1994). In the health sphere, major depression is associated with a substantial loss of quality of life and increased mortality rates (Buntrock et al., 2014).

Since mood changes can play a crucial role regarding depression and are experienced by many individuals on a daily basis, we focus on the prediction of the mood level in this study. The changes of mood can be affected by executed activities and varying events throughout the day (Weinstein and Mermelstein, 2008).

These events and subsequently mood levels have a stake in determining well-being and cognitive functions such as problem solving (Isen et al., 1987), creativity, and the performance level (Nadler, Rabi, and Minda, 2010). Because various activities from walking a dog, to volunteering, cleaning the house, or having a drink out with friends affect mood in different and complex ways (Weinstein and Mermelstein, 2008), we attempt to analyze the effects that different activities can have on the mood level of an individual. Despite the fact that the importance of daily activities for a person's happiness and well-being is well known (Tadic et al., 2013), there is no specific indicator of how different activities explicitly affect the mood level of a client. Although it is recognized that changes in mood exist - the actual origin of them and how certain activities are connected with mood changes is not yet understood completely (Weinstein and Mermelstein, 2008). In that context, we hope to provide further insight.

For our approach, we utilize diary data that is provided by participants of an online depression treatment (Buntrock et al., 2014). Diary data is often collected using Ecological Momentary Assessments (EMA) (Iida et al., 2012; Smyth and Stone, 2003). These methods and online healthcare treatments have been established in order to treat depression and other mental disorders; resulting in the collection of a new kind of data. EMA methods are one option to collect data on symptoms and behavior close in time to a clients experience - and most importantly - in their natural environment (Iida et al., 2012). These methods and Internet-based treatment in general can potentially lead to an increase of quality of treatment by providing deeper insight into the daily lives of the participants (Eysenbach, 2001; Iida et al., 2012).

The field of Information Systems (IS) can contribute to gaining insight into individual behavior and E-Mental-Health in different ways (Agarwal and Dhar, 2014). Developing statistical models and applying techniques such as text-mining for the analysis of data represent powerful ways of improving the understanding of clients in therapeutic treatments. They simultaneously provide the opportunity to reveal relationships and effects between psychological concepts (Agarwal and Dhar, 2014) and can therefore inform decision-making in the E-Health sector (Jardim, 2013).

In this study, we utilize text-mining techniques in order to categorize free text diary data and use partial ordered logit models to subsequently predict the mood level. By doing so, we illustrate the importance of accounting for heterogeneity among individual clients. For parameter estimation, Markov Chain Monte Carlo (MCMC) techniques are employed. Besides studying the relationship between activities and the mood level, we contribute to the field of Information Systems by providing a mixed method approach to analyze diary data. We can further support the decision-making process in online therapy by, for example, offering important insights into *how* and *when* to intervene in online therapy.

In the following chapters, we first discuss related literature. We then present the experimental setting of our study including a brief description of the dataset, introduce the predictors, and describe our text-mining approach and model development. Finally, we illustrate the results, point out some limitations, and conclude our work.

2 Related Literature

A low mood level can potentially result in severe depression (Minden, 2000). An entire set of behavioral patterns are affected by mood changes and a low mood level. Since we know that different activities influence the mood in various ways (Weinstein and Mermelstein, 2008), it is increasingly important to study and evaluate the impact of daily events on the mood level of participants. In this chapter, we demonstrate the importance of this topic in general and illustrate the state-of-the-art regarding mood changes. We do not specify activity categories in this chapter but illustrate general relationships of psychological concepts and mood.

According to early research in the field of behavioral theories, pleasant events have great potential of improving the mood level of individuals and general well-being (Grosscup and Lewinsohn, 1980; Lewinsohn and Amenson, 1978). Researchers have also identified the existence of a relationship between specific activities such as exercise (Wang et al., 2012) or social activities (Byrne and Byrne, 1993; Clark and Watson, 1988) and the mood level of individuals. In recent years, the impact of low moods was further

investigated whereas serious consequences could be identified. In the case of experiencing long-lasting and “excessive” low mood levels, severe depression can occur (Nesse, 2000). This state of enduring negative mood can subsequently lead to low self-esteem, pessimism, sadness, loss of pleasure in favorite activities, and even an increased risk for cardiovascular disease (Both et al., 2008; Nesse, 2000; Penninx et al., 2001). Besides that, Donaldson and Lam (2004) find a relationship between depression, mood, rumination, and problem solution skills. Specifically, they reveal that depressed and ruminative participants with a lower mood level are more challenged by problems and deliver less effective solutions compared to less ruminative individuals. Additionally, Reis et al. (2000) utilize hierarchical linear models in order to analyze factors that influence emotional well-being. Their results indicate that three concepts are crucial for an individual - autonomy, competence, and relatedness. They also find that the mood level is explicitly increasing on the weekend and decreasing on Mondays. The latter finding is also consistent with the results of Becker et al. (2016) who seek to predict the mood level of 27 healthy Dutch students by utilizing smartphone-based data and a varying set of statistical methods.

Regarding our approach of categorizing free text into activity categories, we are not the first to implement text-mining techniques. Balog, Mishne, and Rijke (2006), for example, provide solutions for determining mood changes and irregularities in blog posts. Their work compares corpus frequencies of terms which lead to an identification of the decisive factors regarding mood changes. Kramer, Guillory, and Hancock (2014) utilize bag-of-words techniques (Linguistic Inquiry and Word Count) and study how emotional posts spread on Facebook. They find that a reduction in positive news leads to less positive and more negative posts by users and vice versa.

Improving predictions of psychological concepts such as mood can lead to essential benefits for clients and reduce health care costs (McMahon, 2014). Since it is often difficult for therapists to predict specific outcomes for patients (Hannan et al., 2005), computerized methods can help and support the decision-making process (Garg et al., 2005). Bright et al. (2012), for example, found that clinical decision support can lead to improved preventive care services. Furthermore, various researchers utilize predictive models in the field of E-Mental-Health in order to reveal relationships between concepts or investigate the acceptance of technological systems (Chih et al., 2014; Hah and Bharadwaj, 2012; Hippisley-Cox et al., 2008; Wilson and Lankton, 2004). Therefore it is increasingly important to develop approaches and models in order to further support the therapist’s work and aim to provide efficient tools that can enhance decision processes and eventually individual outcomes. To the best of our knowledge, there is no study that seeks to categorize free text diary data from interventions and simultaneously predicts specific outcomes.

3 Setting, Predictors, & Extracting Activities

The dataset utilized in our research is acquired from two separate trials of an online depression treatment that “evaluate the efficacy of a newly developed guided self-help Internet-based intervention compared to an online psychoeducation on depression” (Buntrock et al., 2014; Ebert et al., 2014). The participants are recruited from the German population via the GET.ON¹ research website. The dataset represents the responses of 440 clients who are 18 years or older, suffer from subthreshold depression, do not have a major depressive episode, and have Internet access. Participants who have a history of psychotic disorders, currently receive psychotherapy, or show a notable suicidal risk are excluded (Buntrock et al., 2014; Ebert et al., 2014). All clients gave their informed consent. Our dataset is based on an activity diary that has been kept by the participants; the data has been gathered through a secured online-based assessment system (Buntrock et al., 2014). In this diary, the clients specify their daily activities as free text and simultaneously report their corresponding individual mood level once a day. In total, we received 9,192 diary entries. Most of the analyzed clients are female (76.2%). The majority (82.4%) of participants are employed (at least part-time) and the average age is 45 years (SD=11.5).

¹ <http://www.geton-training.de/>

3.1 Activity Categories

Work Related Activities

In this study, work related activities are defined as all actions that can be linked to duties on the job; examples for this category can be 'call at work' or 'office meeting'. Work related activities can have positive or negative influences on individuals based on the type of the experience. Great achievements at work, for example, can increase the mood level and *bad* experiences at work decrease the mood state. Stone (1987) and Stewart and Barling (1996) state that work related stress factors are strongly associated with negative mood and especially when not being able to detach from work, they can also be a crucial aspect for recovery processes (Cropley and Zijlstra, 2011). On the other hand, Tadic et al. (2013) find that participation in daily work related activities increases the chance of being in a momentary state of happiness. One reason for this finding could be the fact that work related activities foster cognitive abilities that in turn can result in greater achievements at work. Interested in the general effects work related activities have on mood, we examine the effects of *good* and *bad* perceived work related activities on the mood level. We hypothesize negative effects from these events because we assume that the continuous stress factor of work potentially outweighs possible momentary feelings of satisfaction that arise out of great work outcomes.

Recreational Activities

Recreational activities aim to rebuild psychological resources (Rook and Zijlstra, 2006) and negative effects that result from exertion (Demerouti et al., 2012). These activities can potentially increase life satisfaction, distract from work stress, and are an important factor for the sleep quality of an individual (Sluiter et al., 2003). With work and sleep taking up a large amount of an individual's day, it is more important to find other activities that help to cope with the daily stress many individuals experience. Thus, how an individual spends alone or leisure time is important for the recovery process (Cropley and Zijlstra, 2011) and can furthermore support overcoming daily stress and in turn, preventing low mood levels (Qian, Yarnal, and Almeida, 2014). In our data, we define recreational activities as leisure time activities. The reported text fields are only assigned to the recreational activity category if they are executed completely alone (otherwise they would be assigned to the category social activity which will be introduced below). We expect recreational activities to have a positive effect on the mood level.

Necessary Activities

We define necessary activities as the kind of action that is frequently needed in an individual's life. Examples of necessary activities are grocery shopping and household chores such as cleaning and vacuuming. These activities do not necessarily need to be perceived as negative - however, they can often be *unwanted* or tedious activities that require energy and are more likely to decrease the mood level of an individual (Bolger et al., 1989). We hypothesize negative influences on the mood level from this activity category.

Exercise

Physical activity can be defined as any movement that requires "energy expenditure". Exercise is a more structured way of physical activity and seeks to increase physical fitness (Caspersen, Powell, and Christenson, 1985). However, in this study, we use the terms interchangeably. Previous literature widely assumes that both exercise and physical activity in general can influence the psychological well-being and happiness of individuals positively and can further even benefit the individual mood state (Byrne and Byrne, 1993; Kanning and Schlicht, 2010; Wang et al., 2012). Netz and Lidor (2003) also show that clients are often "less anxious, tense, depressed, angry, and confused after exercising than before". Therefore, we hypothesize positive effects from physical activities on the mood level.

Sickness

Sickness can lead to decreasing levels of mood and previous literature already indicates that life threatening diseases such as stroke and cancer influence the mood level negatively (McCorkle and Quint-Benoliel, 1983; Robinson et al., 1984). But how does the state of “normal and every day life sickness” such as a cold or a headache influence the mood level? In an attempt to answer this question, we use this activity category as predictor to measure its influence and predict the individual mood level. We expect this category to have a negative influence on the mood.

Sleep Related Activities

Sleep loss can be associated with changes of mood, fatigue, and stress (Dinges et al., 1997; Rosen et al., 2006). But sleep can also be perceived as a state of relaxation and rest when experiencing *good* sleep quality and an appropriate amount of sleep. Under that condition, sleep can be used to recover and improve the mood level (Bolger et al., 1989; Dinges et al., 1997). Therefore, we are interested in how sleep affects the mood level of the participants. We are uncertain of how sleep related activities affect the mood level.

Rumination

We define rumination as a state of repetitively reflecting and thinking about upsetting situations and life in general. Rumination can possibly lead to a multitude of negative emotions (Thomsen et al., 2003). Furthermore, depressed individuals are more “self-focused” than non depressed individuals (Ingram and Smith, 1984; Larsen and Cowan, 1988). Ruminative responses, a specific type of self-focusing, represents the state of primarily thinking about depressive symptoms and their consequences (Nolen-Hoeksema and Morrow, 1993). Constantly being reminded of those symptoms and their aftermath can have a negative effect on the mood level of individuals. On the other hand, ruminative phases might provide insight and support to overcome personal problems (Watkins and Baracaia, 2001). In our analysis, the free text fields are assigned to the rumination category whenever states of *serious thoughts* are reported. Therefore, we include positive as well as negative thoughts in our rumination category. Nevertheless, we hypothesize negative effects on the mood level from this category.

Social Activities

Social activities have been shown to result in an increased “positive affect” for individuals (Weinstein and Mermelstein, 2008). Previous research finds a consistent positive relationship between social activities and a person’s mood level (Clark and Watson, 1988; David et al., 1997). Moreover, social activeness can also lead to a general increased well-being and improve negative mood states (Weinstein and Mermelstein, 2008). In our analysis, we define social activities as a state of spare or leisure time where at least one person is present besides the participant. These social activities can either be *good* or *bad* experiences. We expect positive effects from social activities on the individual mood level.

3.2 Text Mining: Extracting Activities

We seek to categorize free text diary data and apply various statistical models in order to predict the individual mood level of the clients. The aim of this chapter is to demonstrate how we categorize the free text into the above specified activity categories. For this purpose, we utilize a bag-of-words (BoW) approach and extent the results by applying recurrent neuronal networks (RNN) (Elman, 1990). We use the RNN extension in order to categorize free texts that have not yet been classified by the BoW technique. The outcomes of both are then compared by their predictive performance. Figure 1 illustrates our approach.

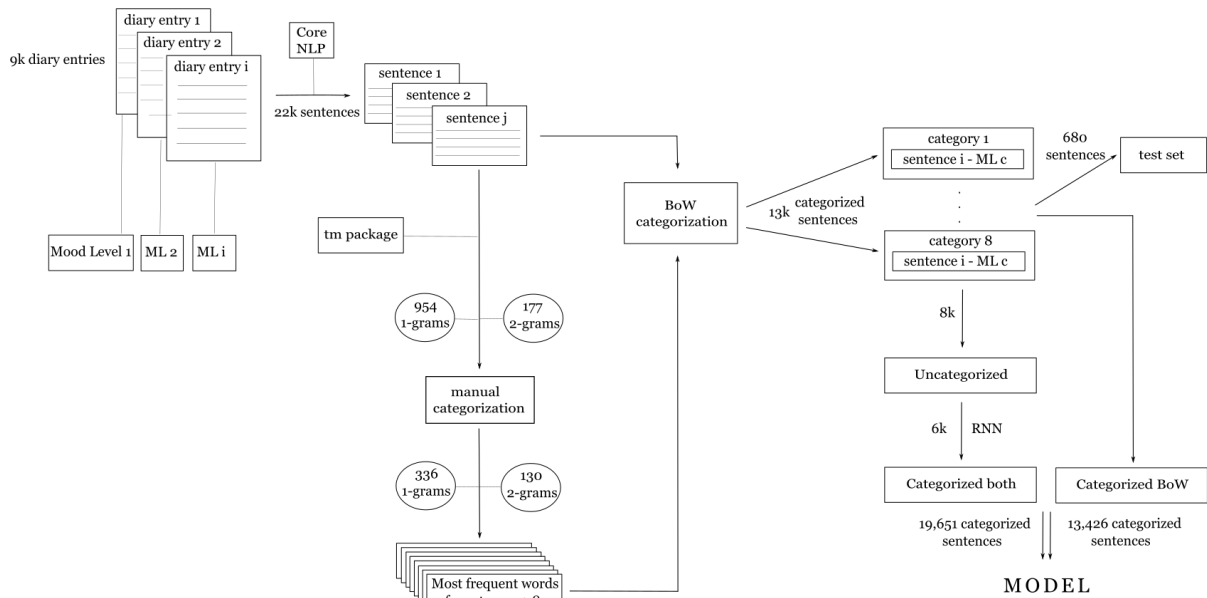


Figure 1. Process of the text-mining approaches for the categorization of diary entries

First, we separate the diary entries into multiple sentences by using the NLP package (Hornik, 2016). The separation of sentences appears necessary because the extent and format of the content in the diary entries varies tremendously. Some clients only provide keywords whereas others state short paragraphs for their daily activities. This process results in 21,598 different sentences. Afterwards, we convert the free text to lower case and remove punctuation, numbers, and stop words (words that do not have any contribution in content, i.e. here, too, nor, about, etc.) by utilizing the `tm` package (Feinerer, Hornik, and Meyer, 2008). In a next step, we identify the most frequent 2-grams and 1-grams and require that they appear at least 10 times in the corpus specified above. The 177 most frequent 2-grams and the 954 most frequent 1-grams are then manually inspected. Specifically, two authors independently categorize the most frequent 1- and 2-grams into the previously defined activity categories. Only the 1- and 2-grams that are assigned identically by both authors (336 1-grams and 130 2-grams) are utilized for the BoW technique. To measure the inter-rater agreement rate, we calculate Cohen's Kappa: For the 1-grams, we achieve a value of .57. According to Landis and Koch (2008), this value can be considered to be a "Moderate" agreement. For the 2-grams, the Cohen's kappa coefficient is .75 ("Substantial") (Landis and Koch, 2008); it achieves a higher kappa coefficient because it includes more context information.

The algorithm then searches for the n-grams in the free text fields reported by the participants and assigns them to the activity categories. Whenever a sentence is connected with various categories, the sentence is assigned multiple times. This method results in 13,426 categorized sentences. Since 8,032 sentences cannot be categorized by the previously described approach (they do not contain any of the n-grams), we explore the predictive power of a recurrent neural network in this context. To do so, we use the 13,426 categorized sentences to train the recurrent neuronal network.

Why do we choose RNN? RNN architectures have been shown to produce strong results in language processing (Kombrink et al., 2011). One reason for that is the RNN's capability of word embedding, this is, each word is represented as a vector and the value of this vector is changed during learning. After the learning phase, similar words of the same category are in proximity to each other in the vector space. This fact enables RNNs to extend the available vocabulary for classifying further sentences.

The RNN is implemented as an Elman network that consists of three layers: the input, hidden, and output layer (Elman, 1990). In this network, each word is represented as a vector and presented to the input layer. In the hidden layer, the input is combined with the previous output of the hidden layer. This result is then redirected into so called "context units". These context units model a temporal memory that

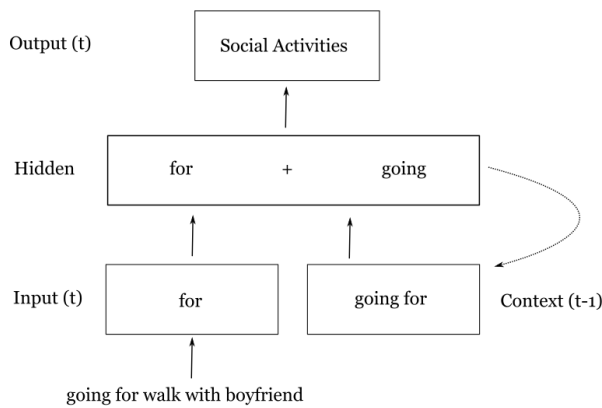


Figure 2. Visualization of the Elman Network

allows the consideration of word sequences. The word-vectors are then sequentially being presented to the neuronal network that subsequently tries to estimate the category of the sentence (output layer). Figure 2 illustrates an example of the classification process of the neuronal network. In this case, the first word that is presented to the network is “going”. The word vector is combined with the content of the context unit in the hidden layer. For the first word, the context layer consist of zeros and has no influence because no word was previously presented. The next word, which is the word “for”, is combined with the previous result of the hidden layer. This specific step is represented in Figure 2. After this step, the context unit consists of a vector representing both words. This process is repeated for each word of the sentence. In the end, the output layer estimates the probability for each category. The category with the highest probability is subsequently selected. The RNN classifies 6,225 sentences that are not already assigned by the BoW technique. In the end, 1,807 sentences are not determined, because these sentences consist of words that do not appear in the 13,426 sentences used for training purposes. The results of both approaches are then merged and utilized as input for the statistical model described in the next section.

4 Model Development

For analyzing the effects of the activity categories on the individual mood level and predicting specific outcomes, we use a partial ordered logit model and employ MCMC techniques for estimating the parameters. It is important to consider that the effects of activities on the mood level also depend on factors within the individuals and can therefore be influenced by exclusive personal and behavioral factors (Gable, Reis, and Elliot, 2000; Weinstein and Mermelstein, 2008). Therefore, heterogeneity among clients can be an important aspect in statistical analyses. By developing multiple models with varying levels of heterogeneity among participants, we not only seek to compare our models and demonstrate the importance of heterogeneity, but achieve a greater prediction performance. We hypothesize that the results become more accurate when allowing for more heterogeneity in the model. In the following, we iteratively illustrate the utilized models and their modifications which account for an increasing amount of heterogeneity.

The dependent variable in this analysis is the mood level on a scale from one to ten. Even though the scores on the scale are ranked, the “real” space between them remains unidentified and cannot be interpreted as real numbers (Norusis, 2010). Ordered logit models address this challenge and are often used in research when ordinal outcomes are involved (Liu and Koirala, 2012).

$$\theta_{ijt} = \frac{P(\text{mood}_{jt} \leq i \mid x_{jt})}{P(\text{mood}_{jt} > i \mid x_{jt})}.$$

In general, this model seeks to estimate the odds θ_{ijt} of being at or below a specific rank of the dependent variable $mood_{jt}$ given the data x_{jt} for each rank i , a specific client j , and every repeated measurement at time t . Here, $mood_{jt}$ represents the EMA response for the mood level for client j at time t . x_{jt} is a vector of length eight (for each activity category) where each element accounts for the number of executed activity for client j at time t . Since specific sentences can be assigned multiple times - also to different activity categories - and the same activity can also be executed more than once a day, multiple elements in the vector x_{jt} can exceed one.

The ordered logit model is based on the proportional odds assumption (Peterson and Harrell, 1990). This assumption represents the belief that the relationship between the independent variables and the outcome of the dependent variable do not depend on the rank (Liu and Koirala, 2012; McCullagh, 1980; Peterson and Harrell, 1990). Specifically, the independent variables (activity categories) have the same effect on the outcome variable across all ranks of the mood level. However, this assumption is often violated in real datasets which can lead to serious problems of interpreting the results (Liu and Koirala, 2012). When the proportional odds assumption is violated, models that allow for varying effects of the predictors among the outcome ranks have been shown to be a better fit compared to the ordered logit model (Liu and Koirala, 2012). Thus, we perform likelihood ratio tests of the proportional odds assumption by utilizing the ordinal package (Christensen, 2015) in R. The results indicate a violation of the proportional odds assumption for the variables Social Activities, Work Related Activities, Necessary Activities, Exercise, Sickness, and Rumination. Based on these results, we then develop a partial ordered logit model. In this case, only some relationships between predictors and the dependent variable do not depend on the rank. Specifically, the variables that violate the proportional odds assumption are allowed to have varying effects among the ranks of the mood level.

$$\begin{aligned} \ln(\theta_{ijt}) = & \alpha_i - (\beta_{social_i} x_{social_{jt}} + \beta_{work_i} x_{work_{jt}} + \beta_{recreational} x_{recreational_{jt}} \\ & + \beta_{necessary_i} x_{necessary_{jt}} + \beta_{exercise_i} x_{exercise_{jt}} + \beta_{sickness_i} x_{sickness_{jt}} \\ & + \beta_{sleep} x_{sleep_{jt}} + \beta_{rumination_i} x_{rumination_{jt}}). \end{aligned} \quad (1)$$

In this partial ordered logit model, α_i represents the boundaries of the categories where $i = 1, \dots, 9$. $x_{[...]}_{jt}$ stands for a specific independent variable (executed activity) of participant j at time t and $\beta_{[...]}$ are the parameters to be estimated for each predictor. The β -terms vary among the ranks for the variables that violate the proportional odds assumption which is indicated by the index i . Equation 1 does not account for any heterogeneity among the clients. The parameters that represent the relationships between the predictors and the dependent variable illustrate the general influences and do not consider any difference in behavior. This is the first version of the model (*Model 1*) we utilize for predicting the mood level of the participants.

Rossi, Allenby, and McCulloch (2012), Farewell (1982), and Johnson (2003) discuss the aspect of “scale usage heterogeneity”. Specifically, this term implies that participants often do not rank a given scale the same way but develop diverse response styles. This varying behavior can lead to a preferred usage of the scale (i.e. only using the middle part of the scale) and even to biased analyses (Rossi, Allenby, and McCulloch, 2012). By implementing client specific cutoffs into α_i , we seek to address the problem of a heterogeneous usage of the scale. Specifically, we sample α_i from a normal distribution. This procedure results in nine specific values that represent the cutoffs for the boundaries of the categories. We then sample user specific cutoffs based on the previously sampled values. This process is indicated by α_{ij} in the following equation:

$$\begin{aligned} \ln(\theta_{ijt}) = & \alpha_{ij} - (\beta_{social_i} x_{social_{jt}} + \beta_{work_i} x_{work_{jt}} + \beta_{recreational} x_{recreational_{jt}} \\ & + \beta_{necessary_i} x_{necessary_{jt}} + \beta_{exercise_i} x_{exercise_{jt}} + \beta_{sickness_i} x_{sickness_{jt}} \\ & + \beta_{sleep} x_{sleep_{jt}} + \beta_{rumination_i} x_{rumination_{jt}}). \end{aligned}$$

This model addresses "scale usage heterogeneity" (*Model 2*). We further hypothesize that not only differences in scale usage exist among the participants. Precisely, we assume varying effects of the items (activities) on different participants and we thus implement client specific β -parameter values to account for the differing influences each concept can have on an individual j . We sample these user specific values from a normal distribution as well. Therefore, *Model 3* is the modification that only accounts for the varying effects the predictors can have on an individual. We also combine both alterations and thus include α and β heterogeneity terms (*Model 4*):

$$\begin{aligned} \ln(\theta_{ijt}) = & \alpha_{ij} - (\beta_{social_{ij}} x_{social_{jt}} + \beta_{work_{ij}} x_{work_{jt}} + \beta_{recreational_{ij}} x_{recreational_{jt}} \\ & + \beta_{necessary_{ij}} x_{necessary_{jt}} + \beta_{exercise_{ij}} x_{exercise_{jt}} + \beta_{sickness_{ij}} x_{sickness_{jt}} \\ & + \beta_{sleep_{ij}} x_{sleep_{jt}} + \beta_{rumination_{ij}} x_{rumination_{jt}}). \end{aligned}$$

For all modifications, the logits for every client j and every response in time t are calculated and then transferred into a probability. Thereupon, a specific outcome for the dependent variable (mood level) is sampled from a categorical distribution based on the individual probabilities. We realize the models in R and include JAGS (Just Another Gibbs Sampler) for MCMC sampling (Plummer, 2003). We implement three chains in JAGS to create three independent samples from the posterior distribution. We perform 40,000 iterations when running the MCMC algorithm and store every twentieth draw from the last 20,000 iterations for each of the three chains. In terms of convergence, all chains succeed for the reported variables.

4.1 Prior Settings & Model Comparison

Based on current literature and our assumptions, we implement specific priors for the predictors. We decide to set a weak negative prior for the variables Work Related Activities, Necessary Activities, Sickness, and Rumination. Moreover, we implement a weak positive prior for the variables Social Activities, Recreational Activities, and Exercise. We also set an uninformative prior for the variable Sleep Related Activities because we do not have further information or are deeply assured as to how this variable could influence the mood level. However, by setting a weak prior for the other predictors we allow for high variance. By doing so, we take previous knowledge, findings of related literature, and our assumptions into account but allow the data to have strong influence on the analysis.

Furthermore, we compare our developed models and attempt to obtain information about the necessary levels of heterogeneity among the participants; concurrently finding the model that has the greatest performance in predicting the test dataset. We start by estimating the parameters with the partial ordered logit model, which does not account for heterogeneity among the participants (*Model 1*). Consequently, we implement solely scale usage heterogeneity (*Model 2*; α -terms), only the influences of each psychological concept on an individual (*Model 3*; β -terms), and subsequently we estimate the parameters by implementing both heterogeneity terms (*Model 4*). We compare the models by using the Deviance Information Criterion (DIC) (Spiegelhalter et al., 2002). The DIC incorporates a measure of fit and a measure of model complexity (Berg, Meyer, and Yu, 2004). A smaller DIC value suggests a superior fit to the data. We choose the DIC for model comparison because it is especially suited for Bayesian models that are estimated by MCMC methods and it does not require additional Monte Carlo sampling (Berg, Meyer, and Yu, 2004). This method has been shown to perform adequately regarding a variety of examples (Berg, Meyer, and Yu, 2004; Spiegelhalter, Best, and Carlin, 1998). According to Ando (2007) and Richardson (2002), however, the DIC can be prone to select overfitted models. Thus, we predict the mood level of the individuals in the test dataset based on the varying models and each text-mining approach and then utilize the Root Mean Square Error (RMSE) as well as the Mean Absolute Error (MAE) as performance

indicators. In the following section, we present the results of the model comparison and of our analysis.

5 Results & Discussion

We utilize free text diary data and categorize them into defined activity categories. First, we classify the free text by applying a BoW approach. The resulting dataset is then used as input for partial ordered logit models with different levels of heterogeneity among the participants. We then extend the BoW approach by utilizing RNN techniques that are trained on the already categorized data. This enables us to classify an additional set of free text. Consistently, we repeatedly use the resulting dataset as input for the models and compare model fit and predictive performance of the text-mining procedures and statistical models. Table 1 illustrates the results of the DIC calculation:

Model	DIC (BoW)	DIC (RNN)
Model 1 (No Heterogeneity)	27717.15	33718.62
Model 2 (α Specific Term)	23644.13	28447.73
Model 3 (β Specific Term)	22775.33	27666.42
Model 4 (α Specific Term & β -Term)	22376.95	26950.70

Table 1. Model comparison with different levels of heterogeneity for each text-mining approach, bag-of-words and RNN.

The reason for an increase of the DIC of the RNN extension in comparison to the BoW approach is the number of observations in the different datasets. Therefore, we do not compare the DIC across the text-mining approaches but among the varying statistical models. As we can see, the DIC value is highest for the model without any heterogeneity in both text-mining approaches. This indicates a superior performance of models that account for differences among the clients and illustrates the importance of heterogeneity. Expecting every participant to behave the same way is not realistic and therefore it is important to account for differences among the individuals.

As expected, the model that includes α - and β -terms has the lowest DIC value. Even though the DIC penalizes the number of parameters in the model, the general fit of this model is better to an extent where the number of parameters are not affecting the performance of model 4 compared to the others. Model 3 also appears to be better than model 2. This might indicate that heterogeneity in the β -coefficients produces a better balance between model fit and model complexity. In order to verify these results and achieve an indicator for the predictive performance, we predict the individual mood values for each text-mining approach and model.

For the comparison and execution of an out-of-sample test, we randomly extract mood entries and their corresponding activities from the data before training the model. We select at most one entry for each client, only from users who provide more than one observation, and - of course - only categorized activities. This random process results in 301 selected mood entries (680 sentences). We then predict the mood levels of each observation of the test set and compare the results. We also report performance measures for a so called *Mean Model*; here, we use the average mood level of the training set as predictions for the test dataset (in this case the number 6).

Measure	Model 1 BoW	Model 1 RNN	Model 2 BoW	Model 2 RNN	Model 3 BoW	Model 3 RNN	Model 4 BoW	Model 4 RNN	Mean Model
RMSE	2.32	2.33	1.98	1.98	1.87	1.91	1.81	1.86	1.91
MAE	1.78	1.82	1.48	1.49	1.41	1.41	1.37	1.37	1.53

Table 2. Prediction performance for each model and text-mining approach.

As illustrated in Table 2, we can see that the *Mean Model* produces a greater predictive performance compared to the model without heterogeneity and even compared to the model including scale usage heterogeneity. However, when more heterogeneity terms are accounted for and the complexity of the model simultaneously increases, the prediction performance clearly grows. Table 2 also indicates that the usage of the RNN does not contribute but rather decreases the predictive performance compared to the BoW approach. This can potentially arise because the training data, which is based on the BoW approach, might not be accurate enough for the RNN to generate new knowledge and connections between the words and categories. Thus, the deep learning algorithm might only add noise to the prediction. Another reason for this finding could be that users often specify their activities as keywords - therefore, the RNN cannot contribute to the prediction. Model 4 for the BoW approach has the greatest prediction performance. Consequently, we choose this model for our analysis regarding the effects of the activity categories on the mood level.

Variable	50%	95% - CI
Work Related Activities	-0.15	(-0.78;0.47)
Recreational Activities	0.54	(-0.57;1.61)
Necessary Activities	-0.07	(-0.65;0.53)
Exercise	0.62	(-0.05;1.26)
Sickness	-4.92	(-6.35;-3.50)
Sleep Related Activities	-0.25	(-2.14;1.67)
Rumination	-5.47	(-7.02;-3.96)
Social Activities	1.50	(1.03;1.98)

Table 3. Estimated model parameters (significant parameters in bold).

As illustrated in Table 3, we find that the category Sickness has a strong negative and significant effect on mood. When being sick, it is a logical assumption and might even be natural to have a lower mood level. Furthermore, our analysis suggest that the category Rumination affects the mood level in a negative way. This can be due to the fact that individuals tend to think more about their problems and reflect on *bad* experiences rather than on *good* experiences. Therefore, negative events outweigh the positive in the stated ruminating activities. We further find that social activities have a significant positive effect on the mood level. This finding is consistent with previous research (Clark and Watson, 1988; David et al., 1997; Sonnentag, 2001; Weinstein and Mermelstein, 2008). Spending time and engaging with others, especially when they are of a general happy nature, might help people to cope with their problems. Another reason for this finding might be linked to the uplifting aspect of having some companionship, sharing a moment, and interacting with somebody else either in conversation or an activity; demonstrating the powerful force that comes with connecting. This can be literally giving a friend a ring and exchanging a few words, or calling friends to schedule an in-person meeting. The strong bonds of friendship can mean support and can provide feelings of enlivenment. Therefore, start browsing through your phone's contacts list - it might be time to call up your friends.

The results also indicate a tendency that physical activities influence the individual mood level positively - even though this result is barely insignificant. Previous literature in the field of psychology often reveals positive effects from exercise such as enhanced psychological well-being, reduced anger, and mood improvements in general (Byrne and Byrne, 1993; Kanning and Schlicht, 2010; Netz and Lidor, 2003; Yeung, 1996). However, we expected a stronger and significant influence from physical activities.

The rest of the predictors show insignificant results. Especially surprising are the results for the category Recreational Activities since we expected a strong positive and significant influence because activities that are directly chosen by an individual are beneficial; he/she would not have chosen that specific activity otherwise. The insignificance for necessary activities might be due to the fact that individuals perceive necessary activities differently. Some clients might enjoy grocery shopping whereas others do experience

this activity as a chore. Furthermore, sleep related activities could be insignificant because individuals might not perceive a bad sleep experience as important enough to report. Therefore, a reason for the insignificance of the predictors is certainly related to the differences in behavior among the participants. Some individuals, for instance, might feel rewarded to a certain degree after they have finished up duties and therefore receive positive moods whereas others experience certain activities more as an ordeal. Thus, we emphasize the importance of individual preferences and heterogeneity by implementing parameters for every participant in the model and demonstrate how the performance level of the utilized models, indicated by the prediction performance, increases the more heterogeneity is implemented. Additionally, some of our findings are consistent with our hypotheses. We can confirm that daily activities, especially social contacts, rumination, and sickness, do influence the mood level of individuals, which is consistent with literature in the field of psychology (Weinstein and Mermelstein, 2008).

6 Limitations & Conclusion

We analyze the effects of daily activities on the individual mood level, predict the mood of the participants, and simultaneously compare a BoW text-mining approach including an extension of this method by coupling BoW and RNN. Furthermore, we evaluate statistical models with different levels of heterogeneity among the clients. We do so by developing varying partial ordered logit models and employing MCMC techniques for parameter estimation. Thus, we emphasize the importance of heterogeneity and seek to foreshadow how analyses and their prediction performance can be improved by considering individual behavior. Furthermore, our results support the development of treatment by focusing on factors that negatively influence the mood level, for example sickness and rumination, and concurrently emphasize and reinforce social activities. Gaining deeper insight into the relationship between certain activities and mood offers the opportunity to achieve greater therapeutic success and can additionally provide an indication for individuals who suffer from mood changes and depression. Therefore, the developed model can serve as a decision support tool for the treating therapist in order to enhance the well-being of the individual, improve the quality of therapy strategies as well as the general therapy outcome. The therapist can then make enhanced decisions of *when* and *how* to intervene. Thus, our method can potentially be utilized by researchers and practitioners to develop and extend decision support systems for therapeutic interventions in healthcare.

Besides the implications and insight our analysis provides, we also outline some limitations regarding our research approach. The developed text-mining algorithm, for example, does not classify all reported text fields to the corresponding activity category correctly. Certainly, it is not simple to classify all text fields accurately because they are often hard to assign in terms of ambiguity. Besides that, the definition of our categories can be questioned. Our exercise category, for instance, represents all physical activities. We do not distinguish between type of exercise, type of sickness, or type of leisure activity. Individuals might also perceive necessary activities differently whereas some individuals might consider cooking as recreational activity and others as necessary. This fact can also lead to insignificant results. Thus, more precise definitions and therefore more categories might result in more accurate outcomes, predictions, implications, and insight. Moreover, although our analyzed dataset is comparatively large, we only possess self-reported and optional data from clients. Even though ecological momentary data is perfectly suited for gathering information on experiences, the data is not reported objectively. Developing more accurate “psychological and biological” measures can further enhance analyses and make results more representative (Cropley and Zijlstra, 2011).

Evidently, further room for improvement and more analyses exists. An implementation of additional categories and other factors such as dropout information or other psychological concepts can further improve our analyses. Developing an enhanced text-mining approach can potentially increase prediction performance and at the same time provide a more accurate support system. In the future, we seek to implement such factors, create other techniques to categorize text fields, develop more statistical models to gain deeper insight into the clients’ behavior, reveal relationships between psychological concepts in

order to support and help clients in need, and simultaneously make an attempt to provide guidance for more personalized interventions and an increased therapy success.

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