A happiness degree predictor using the conceptual data structure for deep learning architectures

Francisco Javier Pérez-Benito[a], Patricia Villacampa-Fernández[b,c], J. Alberto Conejero[b], Juan M. García-Gómez[a,*], Esperanza Navarro-Pardo[c]

[a] *Biomedical Data Science Lab. Instituto de Aplicaciones de las Tecnologías de la Información y de las Comunicaciones Avanzadas (ITACA), Universitat Politécnica de Valéncia, Camino de Vera s/n, 46022 Valencia, Spain.*
[b] *Instituto Universitario de Matemática Pura y Aplicada, Universitat Politécnica de Valéncia, Camino de Vera s/n, 46022 Valencia, Spain.*
[c] *Departamento de Psicología Evolutiva y de la Educación, Universitat de Valéncia, Avenida Blasco Ibáñez, 21, 46010 Valencia, Spain.*

Abstract

Background and Objective: Happiness is a universal fundamental human goal. Since the emergence of Positive Psychology, a major focus in psychological research has been to study the role of certain factors in the prediction of happiness. The conventional methodologies are based on linear relationships, such as the commonly used Multivariate Linear Regression (MLR), which may suffer from the lack of representative capacity to the varied psychological features. Using Deep Neural Networks (DNN), we define a *Happiness Degree Predictor* (H-DP) based on the answers to five psychometric standardized questionnaires.

Methods: A Data-Structure driven architecture for DNNs (D-SDNN) is proposed for defining a HDP in which the network architecture enables the conceptual interpretation of psychological factors associated to happiness. Four different neural network configurations have been tested, varying the number of neurons and the presence or absence of bias in the hidden layers. Two metrics for evaluating the influence of conceptual dimensions have been defined and

*Corresponding author

Email addresses: `frapebe@doctor.upv.es` (Francisco Javier Pérez-Benito), `patricia.villacampa@uv.es` (Patricia Villacampa-Fernández), `aconejero@upv.es` (J. Alberto Conejero), `juanmig@ibime.upv.es` (Juan M. García-Gómez), `esperanza.navarro@uv.es` (Esperanza Navarro-Pardo)

computed: one quantifies the influence weight of the conceptual dimension in absolute terms and the other one pinpoints the direction (positive or negative) of the influence.

Materials: A cross-sectional survey targeting non-institutionalized adult population residing in Spain was completed by 823 cases. The total of 111 elements of the survey are grouped by socio-demographic data and by five psychometric scales (Brief COPE Inventory, EPQR-A, GHQ-28, MOS-SSS and SDHS) measuring several psychological factors acting one as the outcome (SDHS) and the four others as predictors.

Results: Our D-SDNN approach provided a better outcome (MSE: $1.46 \cdot 10^{-2}$) than MLR (MSE: $2.30 \cdot 10^{-2}$), hence improving by 37% the predictive accuracy, and allowing to simulate the conceptual structure.

Conclusions: We observe a better performance of Deep Neural Networks (DNN) with respect to traditional methodologies. This demonstrates its capability to capture the conceptual structure for predicting happiness degree through psychological variables assessed by standardized questionnaires. It also permits to estimate the influence of each factor on the outcome without assuming a linear relationship.
Keywords: Deep Learning, Data-structure driven deep neural network (D-SDNN), Happiness, Happiness-Degree Predictor (H-DP)

---

1. Introduction

The pursuit of happiness is a universal - both cultural and time wise - core driver of human behaviour. Since ancient times pivotal and referent philosophical figures, as for example Aristotle [1] from West or Zhuangzi [2] from East, devoted much of their work to the idea of happiness as an ultimate purpose of human existence. The major proof that this consciousness pursuit of happiness

[1] *Happiness depends on ourselves.* Aristotle

[2] *Happiness is the absence of the striving for happiness.* Zhuangzi

should be considered as a fundamental human goal is the resolution adopted by the United Nations General Assembly on June 28th, 2012 where March, 20th was proclaimed the International Day of Happiness:

> *Recognizing the relevance of happiness and well-being as universal goals and aspirations in the lives of human beings around the world and the importance of their recognition in public policy objectives.*
>
> *Recognizing also the need for a more inclusive, equitable and balanced approach to economic growth that promotes sustainable development, poverty eradication, happiness and the well-being of all peoples [1].*

Consistent with this resolution, the United Nations (UN) has created a civilian based movement for a happier world [2, 3], and took the lead to well-being and happiness as a principal aim in the development and launch of the 17 Sustainable Development Goals of the 2030 Agenda for Sustainable Development [4, 5].

1.1. Happiness-Degree Predictor

Since the emergence of Positive Psychology [6] as the scientific study of factors that lead humans – both at the individual and collective level– to thrive, the research community has consistently built up the evidence-based knowledge about the so-called happiness or subjective well-being [7–14].

Happiness and depression are terms employed in daily life to denote affective states and mood swings, which are reliably represented as falling at opposite ends of a bipolar valence continuum [15, 16]. For illustrative purposes, a graphical representation of the emotional valence spectrum is displayed in Figure 1.

Figure 1: Emotional valence spectrum

As it can be seen, depression is allocated at the very end of the negative affect side whereas happiness is placed at the opposite one. This implies that happiness is not just the absence of negative mood and affective states, but also the presence of positive ones.

Regarding happiness *predictors*, existent research has found *psychological factors* such as stress coping strategies [17, 18], perceived social support [19–22] or personality [23–26] to have a considerable weight in its emergence. Up to now, the traditional methodological approach employed for happiness degree prediction has been a Multivariate Linear Regression (MLR) [27].

Emerging paradigms, novel approaches, and tools such as deep learning are becoming increasingly influential in psychological research as in the case of emotion recognition [28–30], sentiment analysis and/or classification [31–33]. It is worth to mention that both topics were endorsed in recent special issues in the last years [34–36] demonstrating the significance of the study and enabling us to avoid one of the pressing constraints of MLR that is the assumption of a linear relationship between the predictors (psychological factors) and the outcome (happiness degree).

Recent studies in sentiment analysis enclosed inside the field of psychology show the tendency to monitor the state of the people through social network activity, image/video and sentence classification [32, 37–39]. These researches show the use of convolutional deep learning approaches which present a better behaviour for feature extraction and selection. Our study aims to mimic –without assuming any linear relationship– the structure of a set of psychometric scales which are conformed by structured data with prediction and interpretation purposes, becoming unnecessary the use of the convolutional technology because of the nature of data.

1.2. Motivation of present study

The main objective of our work is to define a *Happiness Degree Predictor* (H-DP) that permits to obtain information of the most significant factors influencing happiness. In particular, this will permit to test the efficiency of increasingly popular regression deep-learning approach in the prediction of Happiness measured in terms of the psychometric *Short Depression-Happiness Scale* (SDHS).

For this purpose, we propose the construction of an intuitive Data-Structure driven Deep Neural Network (D-SDNN) based on the conceptual structure of the psychological factors -emotional distress, personality, stress coping strategies, and perceived social support- for supervised learning. The current technique of deep learning is believed to have many different advantages [39, 40]. Among them, D-SDNN's are expected to improve the correctness of prediction respect to the ones given by MLR, as well as to monitor the influence –weight– that different conceptual dimensions –psychological factors– have in the emergence of a certain degree of happiness and hence in the H-DP.

The rest of the paper is organized as follows. First, in Section 2, we provide a short description of the psychometric scales employed to measure the psychological factors used by our D-SDNN. Next, the sample and the data preprocessing procedure are presented. Section 3 is devoted to the conceptual scheme and principal features of D-SDNNs. Four D-SDNNs have been trained. Section 4 presents our results using a real data and compared to MLR. Impact, contributions, limitations and future work are presented in Section 5. Finally, a short conclusion is drawn in Section 6.

2. Materials

2.1. Sample: Issues to consider

Psychological and mental wellbeing has only recently been measurable with valid and reliable measures, but happiness can be understood as satisfaction with life, depression absence, stable extraversion, etc., so even they do not constitute the same construct may be found strong relationships between them. Literature reveals that a lot of sources may influence in happiness, the strongest effects are due to marital status, the relation with the employment, occupational status, leisure and competencies of health and social skills [41]. So, in this paper we have used a specific instrument to assess happiness and we have included other related and different constructs (as coping strategies, personality, emotional distress and social support) in the model in order to design a whole picture of mental and psychological status of the sample.

2.1.1. Description of the sample

The target of the cross-sectional survey was the non-institutionalized adult population residing in Valencia. A total of 823 participants completed the survey, 59.8% of whom were women. The mean age was 46 ($\pm$21.1) ranging from 18 to 92 years old. Regarding the educational level of the sample, a 12.2% had not received formal education, 25.8% primary education, 28.7% secondary education, and the remaining 33.3% had received –or were currently receiving– tertiary education. For what it concerns their marital status, 39% of them were single, 41.4% married, 8.3% separated or divorced, and the remaining 11.3% were widow(er).

2.1.2. Grounds for exclusion

The sample was collected by 76 different interviewers implying that some of the participants were interviewed by more than one person. We took this fact into account in order to avoid incorrect results. In this sense, if the multiple responses of each repeated participant were equal, then the participant was included, being excluded in the other case.

2.2. Descriptions of psychometric scales

Psychometric scales are standardized questionnaires that measure latent variables (psychological factors) through empirical items (behavioral indicators). The procedure of using a psychometric scale comprises a first step where the scale is validated and a second one where its reliability is estimated. In order to be usable, once a scale has been validated in a certain population, its validity does not need to be checked again. However, the reliability of a scale must be checked every time this scale is used over a different sample. There are several indexes to estimate the internal consistency (i.e. reliability) of a scale. The index most commonly employed is the Cronbach's α coefficient [42]. Therefore, we will present below the different psychometric scales employed in this work to measure latent variables. Cronbach's α coefficients obtained for each scale are presented in Section 2.3.

Happiness was measured with the Short Depression-Happiness Scale (SDHS) [16]. It is a 4-point Likert-scale ranging from 0 ("*never*") to 3 ("*often*") with a total of 6 items, 3 of which describe positive feelings (e.g. "*I felt that life was enjoyable*") while three other describe negative feelings –and are hence reverse scored– (e.g. "*I felt cheerless*"). The total score (which may vary between 0 –Depression– and 18 –Happiness–) was computed to obtain the happiness/depression degree for each participant and was employed as gold-standard for supervised-training for the outcome of the D-SDNN.

Coping Strategies are different mental mechanism regarding to manage demands and conflicts and to regulate emotional response and stress. These strategies include the use of personal resources and coping strategies are involved in situations which individuals frequently feel that do not have enough resources or they are not able to answer properly to these demands. Main coping strategies are conductual, cognitive and emotional and could be focussed towards the problem or towards the emotion –that we have at that moment–. Coping Strategies were assessed using the Brief COPE Inventory [43]. It is a 4-point Likert-scale ranging from 1 ("*I usually don't do this at all*") to 4 ("*I usually do this a lot*") with a total of 28 items regrouped in 14 sub-scales of 2 items each: self-distraction, active coping, denial, substance abuse, use of emotional support, use of instrumental support, behavioural disengagement, venting, positive re-framing, planning, humour, religion, and self-blame.

Personality was assessed with the Eysenck Personality Questionnaire Revised-Abbreviated (EPQR-A) [44]. It consists of 4 scales of 6 dichotomous items ("*yes/no*") each that assess neuroticism, extraversion, psychoticism, and sincerity.

Emotional Distress is a feeling that a person or situation is triggering a psychological suffering and could be expresed in different degrees not only cognitive or verbally but through mental or physical symptoms –deppression, anxiety, insomnia, anorexia or poliphagia, upset, vertigo, fatigue, nausea, pain, etc.–. Emotional distress can be interpreted as the opposite status of well-being, happiness, personal satisfaction, welfare, etc. This psychological factor was measured using the 28-item General Health Questionnaire (GHQ-28) [45]. It is a 5-point Likert-scale ranging from 0 ("*not at all*") to 4 ("*much more than usual*") with a total of 28 items regrouped in 4 sub-scales of 7 items each: somatic symptoms, anxiety/insomnia, social dysfunction, and severe depression.

Social Support was assessed with the Medical Outcomes Study (MOS) Social Support Survey (MOS-SSS) [46]. It consists of a first question asking for the number of close friends and close relatives that the person has, plus a 5-point Likert-scale ranging from 1 ("*non of the time*") to 4 ("*all of the time*") with a total of 19 items regrouped into 4 functional support sub-scales of 8, 4, 4, and 3 items per sub-scale. These are: emotional/informational, tangible, affectionate, and positive social interaction.

2.3. Descriptions of Data preprocessing

The reliability is referred to the non-systematic error of the measure. It is a feature of the results and can be influenced by the length of the instrument, the homogeneity of the group measured, etc. [47]. The minimum acceptable value of the reliability coefficient depends on the use made of the instrument [48]. In this sense, we first computed the Cronbach's α coefficients for estimating the internal consistency of the psychometric scales in order to check the reliability work prior to use the data gathered with them. The coefficients obtained are summarized in Table 1. It is considered an acceptable internal consistency for Cronbach's α for values from 0.70. As it can be seen in Table 1, all scales presented a good reliability except for the case of the EPQR-A (that measured personality). Some authors highlight that reliability indices can be influenced by the scale length [49, 50]. Shorter scales usually show lower coefficients than the longer ones, the personality was measured by the abbreviated version of the scale EPQR (the revised scale consist of 100 items while the abbreviated version comprises 24 items) and this may explain the low internal consistency. In any case, we propose the use of the scale but the results regarding this dimension should be interpreted with caution considering the obtained degree of internal consistency.

Psychometric scale	**Cronbach's α coefficient**
SDHS	0.79
Brief COPE Inventory	0.84
EPQR-A	0.42
GHQ-28	0.87
MOS-SSS	0.95

Table 1: Cronbach's α coefficients obtained for each psychometric scale

The variables used in this work can be distinguished between numerical or state ones. We pre-processed them differently according to their nature.

State variables (Marital Status and Level of Education) needed re-codification before the analysis under the assumption: if two states are related, i.e. there exists the possibility of changing from one state to the other, then the codification only differs in one digit, defining an Ordered Binary-Decision Diagram (OBDD) [51] and permiting to use a *dummy* codification [52].

The range of the numerical variables, such as age (discrete data), gender (binary data) and the results of the standardized psychometric scales (continuous data) -including the predictors and the outcome-, are known. We therefore normalized data for deep neural network's inputs according to equation (1), since networks tend to work better when the data are normalized [53].

$$t = (t_{\max} - t_{\min})\frac{x - x_{\min}}{x_{\max} - x_{\min}} + t_{\min}. \quad (1)$$

Here, t represents each input variable for the neural network and x the original value for each variable. Note that $x_{\max} - x_{\min}$ and $t_{\max} - t_{\min}$ represent the range of data collected and neural network's inputs, respectively. The use of data in its original range may provoke a need for comparison of the network's output against the real range, in such case:

$$x = x_{\min} + \frac{(t - t_{\min})(x_{\max} - x_{\min})}{t_{\max} - t_{\min}}. \tag{2}$$

Values $t_{\max} = 1$ and $t_{\min} = 0$ have been taken in order to use logistic activation function (see (3)) in each neuron of the hidden layers.

$$f(x) = \frac{1}{1 + e^{-x}}. \tag{3}$$

3. Methods

3.1. Conceptual scheme

In line with the above objectives mentioned, we have tried to simulate the data conceptual structure in order to gather extra information about the importance of each dimension (i.e. psychological factors) in the H-DP. This architecture can be understood as an ensemble of simpler networks to approximate a function $f : \mathbb{R}^N \longrightarrow \mathbb{R}$. In the context of regression, ensembling some of the neural networks may be better than ensembling all of them [54].

We propose a hierarchical ensembling data driven method for modeling the task in hand. The preconceived data structure has led the layers' ensembling. The items of the psychometric scales employed for measuring the psychological factors used as predictors have been empirically proved to cluster into sub-dimensions and dimensions, i.e. sub-factors and factors [43–46]. We have mimicked this empirically-based conceptual structure in the design of the architecture for our D-SDNN, as it is shown in Table 2 and Figure 2. We may observe that the 105 inputs included have been regrouped into six main domains:

1 - **Interviewer ID**, which is included in order to control for the influence of the person who was in charge of the data gathering.

2 - **Age, Gender, Marital Status and Level of Education** are Socio-Demographic features and therefore grouped into the conceptual dimension *Socio-Demographic Data*.

3 - **The 28 items from the Brief COPE Inventory** are firstly grouped into fourteen conceptual sub-dimensions: *Active Coping*, *Positive Remaining*, *Acceptance*, *Use of Instrumental Support*, *Self-distraction*, *Religion*, *Self Blame*, *Planning*, *Humour*, *Use of Emotional Support*, *Behavioral disengagement*, *Denial*, *Substance Use* and *Venting*. These are finally grouped into the conceptual dimension *Coping Strategies* that is the psychological factor measured by the *Brief COPE Inventory*.

4 - **The 24 items from the EPQR-A** are firstly grouped into four conceptual sub-dimensions: *Neuroticism*, *Extraversion*, *Psychoticism*, and *Sincerity*; joining together to the conceptual dimension *Personality*, which is the psychological factor that the EPQR-A measures.

5 - **The 28 items from the GHQ** are in the first place grouped into four conceptual sub-dimensions: *Somatic Symptoms*, *Anxiety/Insomnia*, *Social Dysfunction* and *Severe Depression*, which finally conform the conceptual dimension *Emotional Distress*. This is the psychological factor measured by the GHQ-28.

6 - **The 20 items from the MOS-SSS** are firstly grouped into five conceptual sub-dimensions: *Emotional Support*, *Material Assistance*, *Social Relationships* and *Affective Support*. They are joined together to the conceptual dimension *Social Support*, which is the psychological factor that the *MOS-SSS* measures. It should be mentioned that the first item of this scale is related to *the number of friends and relatives you can count on* and this goes directly to the conceptual dimension. Furthermore, this item has been normalized by formula (1) taking $x_{\min} = 0$ and $x_{\max}$ the higher value observed in the sample.

PREDICTORS			
Psychometric Scale	**Input/Example of Item**	**Conceptual Sub-dimensions**	**Conceptual Dimensions**
-	Interviewer ID	-	-
-	Age, Sex, Marital Status and level of education	-	Socio-Demographic data
Brief COPE Inventory	*"I've been turning to work or other activities to take my mind off things"*	Self distraction Active coping Denial Substance use Use of emotional support Use of instrumental support Behavioural disengagement Venting Positive remaining Planning Humour Acceptance Religion Self Blame	Coping Strategies
EPQR-A	*"Can you easily get some life into a rather dull party?"*	Neuroticism Extraversion Psychoticism Sincerity	Personality
GHQ-28	*"Have you found everything getting on top of you?"*	Somatic Symptoms Anxiety/Insomnia Social Dysfunction Severe Depression	Emotional distress
MOS-SSS	*"Someone to give you good advice about a crisis"*	Emotional Support Material Assistance Social Relationship Affective Support	Social Support

Table 2: Data Conceptual Structure. The first two columns correspond to networks' inputs. Columns *Conceptual Sub-dimensions* and *Conceptual Dimensions* are materialised to layers of the deep neural networks as it is shown in Figure 2.

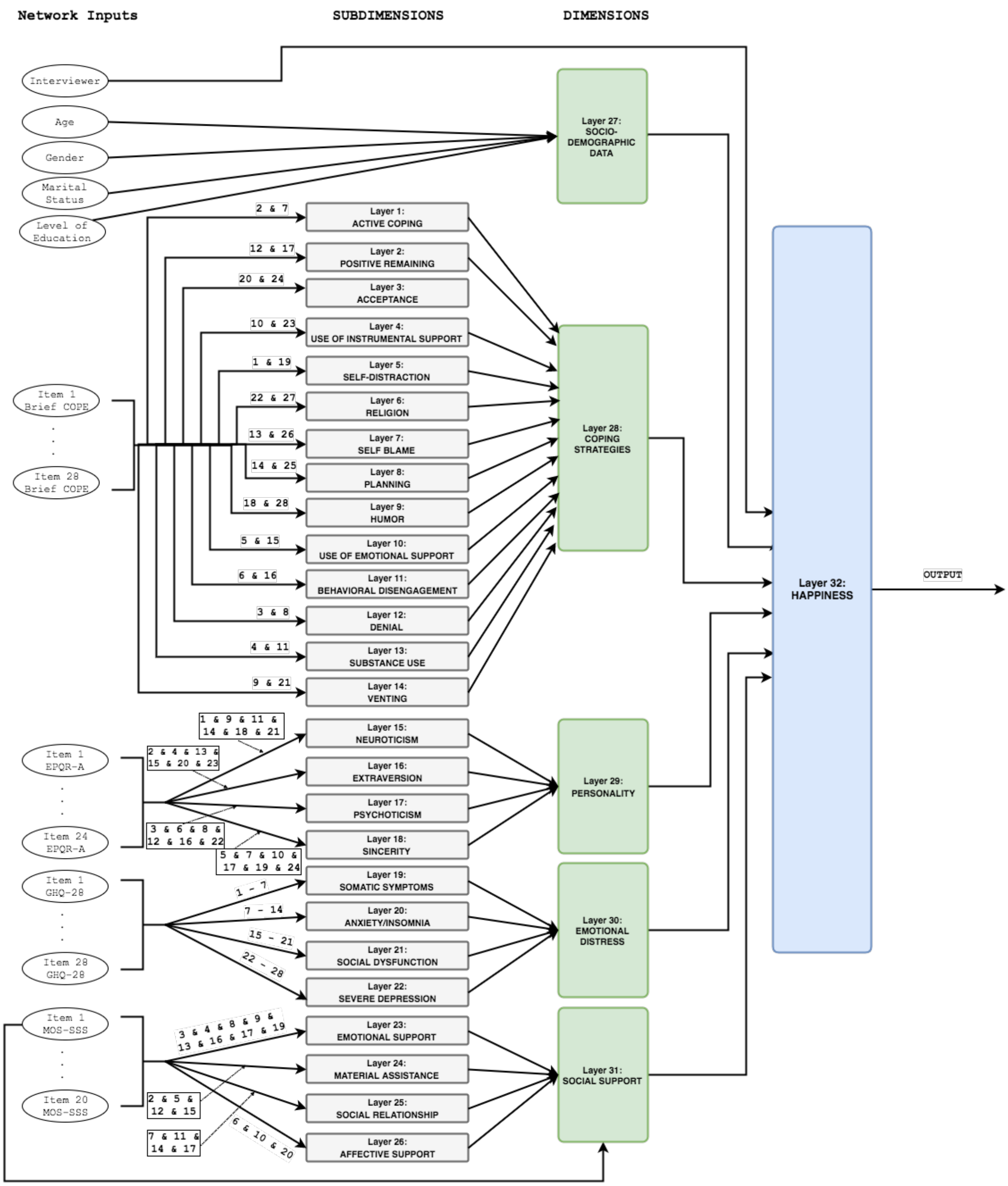


Figure 2: Data-structure driven architecture for our proposed neural networks. The associated number to each arrow, this is arriving to the sub-dimension layers, are related to the number of the items enclosed into the sub-dimension.

3.2. D-SDNN features

By mimicking the conceptual structure presented in Figure 2, we have created 4 deep neural networks (*net1*, *net1b*, *net2* and *net2b*) for supervised learning, in which each conceptual sub-dimension and dimension conforms one hidden layer.

The four neural networks were the result of combining two conditions with two options in each case:

a) the number of neurons per layer (one vs. as many as incoming inputs), and

b) the *Bias/Variance Dilemma* [55] (existence vs. absence of bias in the hidden layer).

A brief of the configuration of each deep neural network is presented in Table 3.

		net1	net1b	net2	net2b
Number of hidden layers		32	32	32	32
Bias in layer		No	Yes	No	Yes
Algorithm for training		L-M	L-M	L-M	L-M
Test for performance		MSE	MSE	MSE	MSE
Initialization algorithm		Random	Random	Nguyen-Widrow	Nguyen-Widrow
	Layers	**net1**	**net1b**	**net2**	**net2b**
Number of Neurons	1 - 14	1	1	2	2
	15 - 18	1	1	6	6
	19 - 22	1	1	7	7
	23	1	1	8	8
	24 - 25	1	1	4	4
	26	1	1	3	3
	27	1	1	4	4
	28	1	1	28	28
	29	1	1	24	24
	30	1	1	28	28
	31	1	1	20	20
	32	1	1	1	1

Table 3: Configuration parameters for the tested D-SDNN. Levenberg-Marquardt algorithm for training has been represented as L-M.

In the sequel we will follow this notation: $f(.)$ denotes the logistic function [56] (see (3)), x the input vector, w_{ij}^{D} the weight of the i_{th} arriving input into the j_{th} neuron of the conceptual dimension/sub-dimension D, b_h the h_{th} bias vector coordinate and [.] has been used to reflect bias existence or absence depending on the settings of each D-SDNN according to Section 3.2. Levenberg-Marquardt has been chosen as training algorithm [57] and MSE as test of performance.

Let $S_1, \ldots, S_{26}$ be the hidden layers that represent the conceptual sub-dimensions of the scales according to Figure 2. We denote by $n_{S_1}, \ldots, n_{S_{26}}$ the number of neurons in each layer, $I_{S_1}, \ldots, I_{S_{26}}$ stand for the set of input indexes arriving at each layer with lengths $n^s_{I_{S_1}}, \ldots, n^s_{I_{S_{26}}}$. Then the output of the j_{th} neuron, $j \in 1, \ldots, n_{S_i}$, into the i_{th} sub-dimension layer $\in S_1, \ldots, S_{26}$ is given by

$$s_{ij} = f\left(\sum_{\substack{h=1\\ l\in I_i}}^{n^s_{I_i}} w_{hj}^{(i)} x_l + [b_h]\right). \tag{4}$$

In the same way, let $D_1, \ldots, D_5$ be the hidden layers that represent the conceptual dimension (Socio-Demographic Data, Coping Strategies, Personality, Emotional Distress, and Social Support, respectively). We call $n_{D_1}, \ldots, n_{D_5}$ the number of neurons in each layer $D_1, \ldots, D_5$. Note that the output of the m_{th} neuron in the dimension layer D_1 is given by

$$d_{D_1 m} = f\left(\sum_{i=1}^{4} w_{im}^{(D_1)} x_{i+1} + [b_i]\right). \tag{5}$$

For the other dimension layers, the output for the m_{th} neuron in the dimension layer D_k, with $k = 2, \ldots, 5$, being $I_{D_2}, \ldots, I_{D_5}$ the sets of outputs $\{s_{ij}\}$ connected to each layer with lengths $n^d_{I_{D_2}}, \ldots, n^d_{I_{D_5}}$, we have

$$d_{km} = f\left(\sum_{\substack{i=1\\ t\in I_k}}^{n^d_{I_k}} w_{im}^{(k)} s_t + [b_i]\right). \tag{6}$$

We point out that D_5 has an additional connection from one of the inputs (see Figure 2) and D_5 must be updated starting from (6), x_{86} is corresponding with the first item of MOS-SSS, which is directly connected to the dimension layer as can be shown in Figure 2.

$$d_{D_5m} = d_{D_5m} + w^{(D_5)}_{(n^d_{I_{D_5}}+1)m} x_{86} + [b_{n_{I_{D_5}}}]. \tag{7}$$

Finally, the last hidden layer in all of our proposed schemes of D-SDNN's has only one neuron. The output can be written as

$$y = f\Bigg(w_1 x_1 + \sum_{i=1}^{n_{D_1}} w_{i+1} d_{D_1 i} + \sum_{i=1}^{n_{D_2}} w_{i+1+n_{D_1}} d_{D_2 i} + \sum_{i=1}^{n_{D_3}} w_{i+1+n_{D_1}+n_{D_2}} d_{D_3 i} +$$

$$+ \sum_{i=1}^{n_{D_4}} w_{i+1+n_{D_1}+n_{D_2} n_{D_3}} d_{D_3 i} + \sum_{i=1}^{n_{D_5}} w_{i+1+n_{D_1}+n_{D_2}+n_{D_3}+n_{D_4}} d_{D_5 i} + [b] \Bigg) \in [0,1]. \tag{8}$$

The regression layer (H) provides a value in $[0, 1]$. With (2) we can denormalize and obtain values $\hat{y} \in [0, 18]$. Goodness of the fitting will be evaluated according to

$$G_T = \sum_{i=1}^{n_T} \frac{(y_i - \hat{y}_i)^2}{n_T}. \tag{9}$$

The testing deviation from the original results will be measured according to

$$\delta_t = \sum_{i=1}^{n_t} \frac{(y_i - \hat{y}_i)^2}{n_t}, \tag{10}$$

where n_T is the training set size and n_t is the testing set size.

Let it be n_{inp} the number of inputs of one neuron of the layer L. In order to measure the global importance of the inputs, we propose the following metrics regarding to weights for each j_{th} neuron in the layer L

$$L_i^{(j)} = \sum_{i=1}^{n_{inp}} \frac{|w_{ij}|}{n_{inp}}, \tag{11}$$

and the positivity or negativity of the relationship is determined by

$$\operatorname{sgn}\left(L_i^{(j)}\right) = \operatorname{sgn}\left(\sum_{i=1}^{n_{inp}} w_{ij}\right). \tag{12}$$

4. Experimental Results

4.1. Training, validating and testing the deep neural networks

For each participant we construct a column vector with the inputs for the deep neural network. The first element represents a numeric identifier for the interviewer. From the 2nd to the 5th elements we have the socio-demographic data about the interviewee. The rest of inputs (from the 6th to the 105th) are the responses to the items that conform the standardized psychometric scales.

We have used 578 instances (column vectors) of the total sample, approximately the 70%, for training the 4 tentatives D-SDNNs. Regarding to the other 30%, a 15% has been used for validating and the last 15% for testing.

The fitting with the training data is better for networks with the same number of neurons as incoming inputs (*net2 and net2b*). This implies that we get a better adaptability of multi-neuron layers networks. Besides, within these 2 networks, we can observe that the biased network *learns* so quickly that it falls into over-fitting problems [58]. So as to, these results raise the suspicion that the best network for the database used in the present study is *net2*.

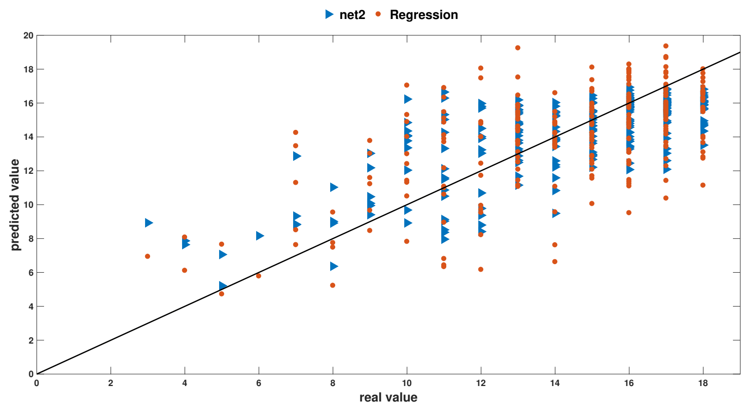
4.2. Comparison of D-SDNNs against Multivariate Linear Regression

4.2.1. Multivariate Linear Regression

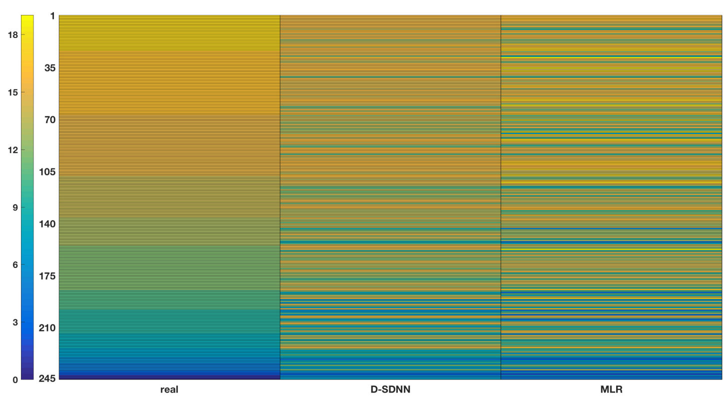
Multivariate Linear Regression (MLR) models are used to predict the value of one or more responses from a set of predictors. MLR's are often used to rate emotional prediction through music [59], effects of colors [60], or neuroimaging [61]. We have constructed a model based on MLR using the inputs of the D-SDNNs as predictors with the purpose of comparison between our D-SDNN's against MLR.

4.2.2. D-SDNNs vs MLR

For the construction of the regression model, we proceed in the same way as in Section 4.1. We choose the same sample used for training the neural networks proposed (approx. 70%) and we have then calculated the predicted values for the other 245 participants (approx 30%). In the same way, we have evaluated our 4 deep neural networks for the 245 cases excluded of the training set with the purpose of comparison against the same cases predicted by MLR (see Figure 3). We have obtained the Mean Square Error (MSE) for each model as shown in Table 4.



(a) net2 vs MLR



(b) Colour Spectrum

Figure 3: Figure (a) presents the comparison of *net2* network against MLR. The points have the value observed as x coordinate, and the predicted value as y. The straight line is $g(x) = x$ which represents the accurate prediction. Figure (b) shows the real, MLR and best fitting D-SDNN color spectrum as indicated in Figure 1. Note that MLR color spectrum produces out of range colors.

	MLR	net1	net2	net1b	net2b
MSE	$2.30 \cdot 10^{-2}$	$1.54 \cdot 10^{-2}$	$1.46 \cdot 10^{-2}$	$1.58 \cdot 10^{-2}$	$1.86 \cdot 10^{-2}$
Improvement %	0	33	**37**	31	19

Table 4: MSE of the models. The percentage of improvement has been calculated taking as basis MLR. Both observed and predicted values used for the calculus of the MSE were normalized between [0,1] according to (1)

.

As it can be seen in Table 4, the models that best behaved were those generated by deep neural networks. Among them, *net2* stands out, presenting an improvement of 37% taking as basis MLR. It is worth noting here again the significant depletion of MSE in the case of *net2b*. The outstanding performance results of *net2* may be considered as a sign suggesting that the bias added to *net2b* originates an over-training that leads to over-fitting issues causing a detriment in the performance test (i.e. and undermined predictive accuracy).

The predictions obtained by using the D-SDNN *net2* and *Regression* produced a MSE for each possible score as shown in Table 5.

SDHS score	**Count of cases**	**MSE net2**	**MSE Regression**
3	1	$4.43 \cdot 10^{-4}$	$1.95 \cdot 10^{-4}$
4	2	$3.55 \cdot 10^{-4}$	$2.65 \cdot 10^{-4}$
5	2	$3.39 \cdot 10^{-5}$	$8.96 \cdot 10^{-5}$
6	2	$5.90 \cdot 10^{-5}$	$6.24 \cdot 10^{-7}$
7	5	10^{-3}	$1.5 \cdot 10^{-3}$
8	4	$1.73 \cdot 10^{-4}$	$1.32 \cdot 10^{-4}$
9	6	$3.87 \cdot 10^{-4}$	$6.46 \cdot 10^{-4}$
10	10	$1.80 \cdot 10^{-3}$	$1.80 \cdot 10^{-3}$
11	16	$1.80 \cdot 10^{-3}$	$2.60 \cdot 10^{-3}$
12	13	$1.20 \cdot 10^{-3}$	$1.90 \cdot 10^{-3}$
13	30	$1.20 \cdot 10^{-3}$	$1.90 \cdot 10^{-3}$
14	19	$7.53 \cdot 10^{-4}$	$1.70 \cdot 10^{-3}$
15	28	$5.37 \cdot 10^{-4}$	$1.40 \cdot 10^{-3}$
16	41	$1.20 \cdot 10^{-3}$	$3.10 \cdot 10^{-3}$
17	43	$1.90 \cdot 10^{-3}$	$3.00 \cdot 10^{-3}$
18	24	$1.80 \cdot 10^{-3}$	$2.80 \cdot 10^{-3}$

Table 5: Best model and MLR MSE for each possible score. It is also shown the number of participants who obtained the score. Nobody obtained scores less than 3.

It can be observed in Table 5 that these scores with more frequency are better predicted by *net2*, i.e. all the scores from 8 to 16 –which represent approximately the 94%– are predicted with more accuracy by *net2*. Besides, those scores that are less frequent present better results for *net2* in cases 5, 6 and 7 improving the percentage of best prediction against MLR up to 97.5%.

In the same way, the regression predictions often produce the highest deviations from the expected value, even exceeding the output range (see Figure 3). This situation is produced by the little adaptability to data of linear models, which is improved using non-linear methods such as the proposed D-SDNN's in the present study.

Finally, we have calculated the differences between the values obtained from each prediction model against the ones observed in order to compare the symmetry and the dispersion of the differences. As shown in Figure 4, the plot corresponding to the differences between *net2* and the *observed values* is the one with the narrowest box and with the closest outliers.

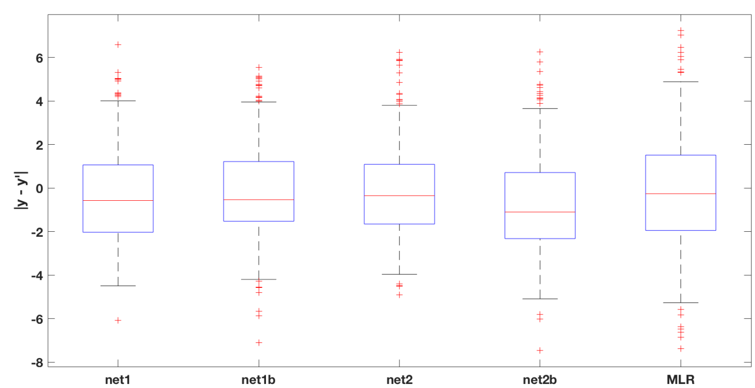


Figure 4: Box-and-whisker plots of differences between predictive models and expected value.

4.3. The last layer weights metrics

The weight of each conceptual dimension quantifies its influence in the prediction. Therefore, weights comprehend all the arriving inputs to the last hidden layer. In order to pinpoint the importance that each psychological factor has on the purpose (happiness degree), we have computed metrics (11) and (12) over each dimension of the best fitting net (*net2*). The results are displayed in Table 6. We observed two key values: the weight of the conceptual dimension's influence in absolute terms ($L_{32}^{(l)}$), and the direction of the influence ($sgn\left(L_{32}^{(l)}\right)$).

Accordingly, the most influential dimension in a positive direction for H-DP appeared to be Social Support, whilst the most influential dimension in a negative direction was Coping Strategies. The significantly less influential dimensions were the Interviewer and Socio-demographic Data.

Conceptual dimensions	$L_{32}^{(l)}$	$sgn\left(L_{32}^{(l)}\right)$	**Interpretation**
Interviewer	0.0311	-	Small negative influence
Socio-demographic data	0.1403	+	Small positive influence
Coping Strategies	0.4476	-	Most negatively influential
Personality	0.4186	+	Positively influential
Emotional Distress	0.3897	-	Negatively influential
Social Support	0.5025	+	Most positively influential

Table 6: Influence metric values in the best prediction.

5. Discussion

5.1. Impact

The aim of the present study was the construction of an intuitive D-SDNN based on a set of psychological factors and their sub-components for supervised learning in order to improve traditional methods for H-DP, which are based on linear relationships [62–64]. As expected, when compared with MLR, D-SDNN's show consistent superiority regardless of their configuration (i.e.. number of neurons per layer, and presence or absence of bias). They also allow us to estimate the weight of each psychological factor on the prediction accuracy of the target. According to the best fitting net (*net2*), the psychological factors least influential in the emergence of Happiness were, as expected, the Interviewer and the Socio-demographic data, whereas the most influential ones were Social Support and Coping Strategies. Although the obtained weights might appear weak, they are not. Indeed, for psychological features, it is not only expected to obtain smaller weights than those from artificial devices, but also desirable. This fact prevents people from psychological determinism, i.e. that psychological factors only explain between a 30 and 50% of the variance allows people to compensate their deficits and to achieve happiness in spite of them.

5.2. Contributions

The contributions of the proposed method for H-DP can be summarized in two key points:

(1.1) An intuitive neural network architecture taking advantage of the data conceptual structure which provides the possibility of drawing conclusions about the importance of each conceptual dimension in the outcome measured.

(1.2) Two metrics that allow us to evaluate and quantify the importance of each conceptual dimension on the outcome in absolute terms as well as in which direction (positive or negative).

It is also worth mentioning that the results shown in Section 4.1 raised the suspicion that multiple-neuron layer network without bias (*net2*) was the one that would yield better performance because of:

(2.1) It provides enough adaptability to changes within sub-dimensions and dimensions, achieving a better fit to the training dataset.

(2.2) The learning rate was controllable enough to fall into problems of overfitting what shows the importance of determining under what circumstances it is beneficial or detrimental the use of bias.

After the evaluation and comparison of the chosen test set against MLR (see Section 4.2), our results demonstrate a consistently superior performance (for the task in hand) for any neural network. We also point out that:

(3.1) MLR may predict out of range values.

(3.2) The best performance for testing set is achieved by *net2*. As shown in Table 4.

Using the metrics proposed in (11) and (12), we have been able to determine the influence of psychological factors in H-DP. The results can be summarized in two main findings:

(4.1) As expected, the people who were in charge of the data collection (i.e. the interviewers) and the socio-demographic characteristics of the participants were the least influential factors for what it concerns H-DP. This means that no matters who asks you, or what your gender, age, marital status or level of education is, your degree of happiness is not likely to be affected.

(4.2) Regarding the role that the studied psychological factors play in the emergence of happiness, we can emphasize:

   a. It can be considered congruent with common sense expectations the significantly high and negative influence of Emotional Distress in the degree of happiness.

   b. By the same token, it is also consistent with literature the significantly high and positive influence of the perceived Social Support in the degree of happiness. According to these findings, the perceived Social Support may be seen as a buffer for the deleterious effect of the Emotional Distress.

   c. The interpretation of the results becomes more controversial for the case of Personality and Coping Strategies. While all the sub-dimensions of the previous factors were in the same direction, is not the case for those of Personality and Coping Strategies (i.e. the influence of some sub-dimensions is expected to be positive, and of some others negative). Concluding that Personality or Coping Strategies, as a whole, have a positive and negative effect, respectively, would very likely be hazardous. One potential explanation is that sub-dimensions, with a positive direction in the case of Personality and with a negative direction in the case of Coping Strategies, have substantially higher weights in absolute terms. However, their respective directions prevail when estimating the general influence of broader dimensions. This would mean that, for example, in the case of Coping Strategies, the adverse effect of Substance abuse or Self blame would be remarkably stronger than the beneficial effect of Humour or Planning.

5.3. Limitations

In the case of multi-neuron layer, the proposed metrics for the evaluation of the inputs' influence, eqs. (11) and (12), can only be conceptually evaluated at the last layer due to the loss of the conceptual scheme within the multi-neuron layers.

By forcing the conceptual structure, the D-SDNNs is not allowed to learn other possible structures that could provide information about the definition of the psychometric scales.

In order to assure the results presented in the present study, the use of the non-abbreviated version of the psychometric scale that measures the personality (EPQR) in the collection of a new data base should be carried out.

5.4. Future work

Insights for future works may be arranged in two main points, in order of priority:

(1) In case of multi-neuron layer D-SDNNs, to look for weights characterizations that allow to measure and monitor inputs' influence into each sub-dimension. Besides, it would be interesting to analyze how outputs of the sub-dimensions influence each dimension until reaching the output of the network.

(2) Applying D-SDNN to longitudinal datasets would allow to monitor the variation of weights over time and hence to underpin whether the influence of psychological factors under study changes through the lifespan.

6. Conclusions

This paper presented a D-SDNN architecture for H-DP from Socio- Demographic Data and a set of psychological factors (Social Support, Personality, Emotional Distress, and Stress Coping Strategies). The four network configurations used showed better results in comparison with MLR, obtaining an improvement of 37% in the best case.

The best predictor was that employing as many neurons –without bias– as questions endorsed in the sub-dimension or dimension. This prediction obtained a best accuracy in the 97.5% of cases of the population studied in comparison with MLR. It only showed a worst performance –compared to MLR– in SDHS scores with low frequency. The most frequent SDHS score that raised lower MSE for MLR was the value 8 with a relative frequency $\frac{4}{823} \approx 0.4\%$.

Furthermore, this method opens the possibility for conceptual interpretations regarding the importance of each predictor considered: in our study results have shown that socio-demographic characteristics such as gender, age or marital status are not likely to affect the degree of happiness whilst other psychological factors as perceived social support or coping strategies play a major role in the emergence and/or maintenance of happiness.

Based on this, it can be concluded that this study is a new approach of a predictive method, which relies on deep learning architectures by mimicking the conceptual data structure, that presents a consistently superior predictive accuracy together with a better conceptual interpretation.

References

[1] United Nations, Resolution adopted by the General Assembly on 28 June 2012, 66/281. International Day of Happiness (Jun. 2012).
URL http://www.un.org/en/ga/search/view_doc.asp?symbol=%20A/RES/66/281 Retrieved on April 28th, 2017.

[2] International Day of Happiness.
URL http://www.dayofhappiness.net/#join Retrieved on April 28th, 2017.

[3] United Nations Foundation, Pharrel Williams tells the world: A Happy Planet = Happy People (2015).
URL http://www.unfoundation.org/news-and-media/press-releases/2015/Pharrell-Williams-Tells-the-World-A-Happy-Planet-Happy-People.html?referrer=https://www.google.es/ Retrieved on April 28th, 2017.

[4] United Nations, International Day of Happiness.
URL http://www.un.org/en/events/happinessday/index.shtml Retrieved on April 28th, 2017.

[5] United Nations, Sustainable Development Goals.
URL http://www.un.org/sustainabledevelopment/development-agenda/ Retrieved on April 28th, 2017.

[6] M. Seligman, M. Csikszentmihalyi, Positive psychology: An introduction, American Psychologist 55 (1) (2000) 5–14.

[7] D. G. Myers, The funds, friends, and faith of happy people., American Psychologist 55 (1) (2000) 56.

[8] E. Diener, The science of happiness and a proposal for a national index, American Psychologist 55 (1) (2000) 34–43.

[9] M. Csikszentmihalyi, If we are so rich, why aren't we happy?, American Psychologist 54 (10) (1999) 821.

[10] S. Lyubomirsky, L. King, E. Diener, The benefits of frequent positive affect: Does happiness lead to success? (2005).

[11] R. Costanza, B. Fisher, S. Ali, C. Beer, L. Bond, R. Boumans, N. L. Danigelis, J. Dickinson, C. Elliott, J. Farley, et al., Quality of life: An approach integrating opportunities, human needs, and subjective well-being, Ecological Economics 61 (2) (2007) 267–276.

[12] S. M. Schueller, M. E. Seligman, Pursuit of pleasure, engagement, and meaning: Relationships to subjective and objective measures of well-being, The Journal of Positive Psychology 5 (4) (2010) 253–263.

[13] N. L. Sin, S. Lyubomirsky, Enhancing well-being and alleviating depressive symptoms with positive psychology interventions: A practice-friendly meta-analysis, Journal of Clinical Psychology 65 (5) (2009) 467–487.

[14] M. E. Seligman, Positive health, Applied Psychology 57 (s1) (2008) 3–18.

[15] S. Joseph, C. A. Lewis, The depression–happiness scale: Reliability and validity of a bipolar self-report scale, Journal of Clinical Psychology 54 (4) (1998) 537–544.

[16] S. Joseph, P. A. Linley, J. Harwood, C. A. Lewis, P. McCollam, Rapid assessment of well-being: The short depression-happiness scale (sdhs), Psychology and psychotherapy: Theory, Research and Practice 77 (4) (2004) 463–478.

[17] M. Rantanen, S. Mauno, U. Kinnunen, J. Rantanen, Do individual coping strategies help or harm in the work–family conflict situation? examining coping as a moderator between work–family conflict and well-being., International Journal of Stress Management 18 (1) (2011) 24.

[18] M. Ojala, How do children cope with global climate change? coping strategies, engagement, and well-being, Journal of Environmental Psychology 32 (3) (2012) 225–233.

[19] L. Lu, J. Shih, Y. Lin, L. Ju, Personal and environmental correlates of happiness, Personality and Individual Differences 23 (3) (1997) 453–462.

[20] Y. Chan, R. P. Lee, Network size, social support and happiness in later life: A comparative study of beijing and hong kong, Journal of Happiness Studies 7 (1) (2006) 87–112.

[21] F. Gülaçtı, The effect of perceived social support on subjective well-being, Procedia-Social and Behavioral Sciences 2 (2) (2010) 3844–3849.

[22] K. L. Siedlecki, T. A. Salthouse, S. Oishi, S. Jeswani, The relationship between social support and subjective well-being across age, Social Indicators Research 117 (2) (2014) 561–576.

[23] A. Furnham, C. R. Brewin, Personality and happiness, Personality and Individual Differences 11 (10) (1990) 1093–1096.

[24] J. Brebner, J. Donaldson, N. Kirby, L. Ward, Relationships between happiness and personality, Personality and Individual Differences 19 (2) (1995) 251–258.

[25] N. Pishva, M. Ghalehban, A. Moradi, L. Hoseini, Personality and happiness, Procedia-Social and Behavioral Sciences 30 (2011) 429–432.

[26] L. Lu, J. Shih, Personality and happiness: Is mental health a mediator?, Personality and Individual Differences 22 (2) (1997) 249–256.

[27] D. Campos, A. Cebolla, S. Quero, J. Bretón-López, C. Botella, J. Soler, J. García-Campayo, M. Demarzo, R. M. Baños, Meditation and happiness: Mindfulness and self-compassion may mediate the meditation–happiness relationship, Personality and Individual Differences 93 (2016) 80–85.

[28] E. M. Schmidt, Y. E. Kim, Learning emotion-based acoustic features with deep belief networks, in: Applications of Signal Processing to Audio and Acoustics (WASPAA), 2011 IEEE Workshop on, IEEE, 2011, pp. 65–68.

[29] K. Han, D. Yu, I. Tashev, Speech emotion recognition using deep neural network and extreme learning machine., in: Interspeech, 2014, pp. 223–227.

[30] Z. Yin, M. Zhao, Y. Wang, J. Yang, J. Zhang, Recognition of emotions using multimodal physiological signals and an ensemble deep learning model, Computer Methods and Programs in Biomedicine 140 (2017) 93–110.

[31] T. Chen, D. Borth, T. Darrell, S.-F. Chang, Deepsentibank: Visual sentiment concept classification with deep convolutional neural networks, arXiv preprint arXiv:1410.8586.
URL https://arxiv.org/abs/1410.8586

[32] Y. Kim, Convolutional neural networks for sentence classification, arXiv preprint arXiv:1408.5882.
URL https://arxiv.org/abs/1408.5882

[33] Q. You, J. Luo, H. Jin, J. Yang, Robust image sentiment analysis using progressively trained and domain transferred deep networks, arXiv preprint arXiv:1509.06041.
URL https://arxiv.org/abs/1509.06041

[34] E. Cambria, B. Schuller, Y. Xia, B. White, New avenues in knowledge bases for natural language processing, Knowledge-Based Systems 108 (2016) 1 – 4, new Avenues in Knowledge Bases for Natural Language Processing. doi:http://dx.doi.org/10.1016/j.knosys.2016.07.025.

[35] E. Cambria, N. Howard, Y. Xia, T. S. Chua, Computational intelligence for big social data analysis [guest editorial], IEEE Computational Intelligence Magazine 11 (3) (2016) 8–9. doi:10.1109/MCI.2016.2572481.

[36] E. Cambria, Affective computing and sentiment analysis, IEEE Intelligent Systems 31 (2) (2016) 102–107. doi:10.1109/MIS.2016.31.

[37] S. Poria, E. Cambria, A. F. Gelbukh, Deep convolutional neural network textual features and multiple kernel learning for utterance-level multimodal sentiment analysis., in: EMNLP, 2015, pp. 2539–2544.

[38] C. N. Dos Santos, M. Gatti, Deep convolutional neural networks for sentiment analysis of short texts., in: COLING, 2014, pp. 69–78.

[39] H. Lin, J. Jia, Q. Guo, Y. Xue, Q. Li, J. Huang, L. Cai, L. Feng, User-level psychological stress detection from social media using deep neural network, in: Proceedings of the 22nd ACM International Conference on Multimedia, ACM, 2014, pp. 507–516.

[40] X. Li, B. Hu, S. Sun, H. Cai, Eeg-based mild depressive detection using feature selection methods and classifiers, Computer Methods and Programs in Biomedicine 136 (2016) 151–161.

[41] M. Argyle, 18 causes and correlates of happiness, Well-being: The foundations of hedonic psychology 353.

[42] J. M. Bland, D. G. Altman, Statistics notes: Cronbach's alpha, British Medical Journal 314 (7080) (1997) 572.

[43] C. S. Carver, You want to measure coping but your protocols too long: Consider the brief cope, International Journal of Behavioral Medicine 4 (1) (1997) 92–100.

[44] L. J. Francis, L. B. Brown, R. Philipchalk, The development of an abbreviated form of the revised eysenck personality questionnaire (epqr-a): Its use among students in england, canada, the usa and australia, Personality and Individual Differences 13 (4) (1992) 443–449.

[45] D. Goldberg, Manual of the ghq, NFER: Windsor.

[46] C. D. Sherbourne, A. L. Stewart, The mos social support survey, Social science & medicine 32 (6) (1991) 705–714.

[47] V. Bonilla, Confiabilidad, en el boletín informativo INEVA en acción, Vol. 2.

[48] I. Lucero, S. Meza, Validación de instrumentos para medir conocimientos, FACENA: Facultad de Ciencias Exactas y Naturales y Agrimesura de la UNNE.

[49] A. Anastasi, Psychological testing.

[50] I. H. Bernstein, J. Nunnally, Psychometric theory, New York: McGraw-Hill. Oliva, TA, Oliver, RL, & MacMillan, IC (1992). A catastrophe model for developing service satisfaction strategies. Journal of Marketing 56 (1994) 83–95.

[51] R. Bryant, Symbolic boolean manipulation with ordered binary-decision diagrams, ACM Computing Surveys (CSUR) 24 (3) (1992) 293–318. `doi:10.1145/136035.136043`.

[52] S. Garavaglia, A. Sharma, A smart guide to dummy variables: Four applications and a macro, in: Proceedings of the Northeast SAS Users Group Conference, 1998, p. 43.

[53] J. V. Tu, Advantages and disadvantages of using artificial neural networks versus logistic regression for predicting medical outcomes, Journal of Clinical Epidemiology 49 (11) (1996) 1225–1231.

[54] Z. . Zhou, J. Wu, W. Tang, Ensembling neural networks: Many could be better than all, Artificial Intelligence 137 (1-2) (2002) 239–263.

[55] S. Geman, E. Bienenstock, R. Doursat, Neural networks and the bias/variance dilemma, Neural Computation 4 (1) (1992) 1–58.

[56] M. I. Jordan, et al., Why the logistic function? a tutorial discussion on probabilities and neural networks (1995).

[57] B. M. Wilamowski, Neural network architectures and learning algorithms, IEEE Industrial Electronics Magazine 3 (4).

[58] S. Lawrence, C. Giles, A. C. Tsoi, Lessons in neural network training: overfitting may be harder than expected, 1997, pp. 540–545.

[59] T. Eerola, O. Lartillot, P. Toiviainen, Prediction of multidimensional emotional ratings in music from audio using multivariate regression models., in: The International Society of Music Information Retrieval, 2009, pp. 621–626.

[60] P. Valdez, A. Mehrabian, Effects of color on emotions., Journal of Experimental Psychology: General 123 (4) (1994) 394.

[61] P. R. Goldin, C. A. Hutcherson, K. N. Ochsner, G. H. Glover, J. D. Gabrieli, J. J. Gross, The neural bases of amusement and sadness: a comparison of block contrast and subject-specific emotion intensity regression approaches, Neuroimage 27 (1) (2005) 26–36.

[62] C. Van Campen, J. Iedema, Are persons with physical disabilities who participate in society healthier and happier? structural equation modelling of objective participation and subjective well-being, Quality of Life Research 16 (4) (2007) 635.

[63] J. Zhang, D. Miao, Y. Sun, R. Xiao, L. Ren, W. Xiao, J. Peng, The impacts of attributional styles and dispositional optimism on subject well-being: A structural equation modelling analysis, Social Indicators Research 119 (2) (2014) 757–769.

[64] R. M. Warner, D. Rasco, Structural equation models for prediction of subjective well-being: Modeling negative affect as a separate outcome, The Journal of Happiness & Well-Being 2 (1) (2014) 34–50.