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Analysis of the symptoms of depression — a neural network approach

Jyotsna Nair*, Satish S. Nair, Javad H. Kashani, John C. Reid, Sanjay I. Mistry, Victor G. Vargas

Departments of Psychiatry and Neurology, School of Medicine, University of Missouri-Columbia, One Hospital Drive, Columbia, MO 65211, USA

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Abstract

The purpose of this study is to determine the individual contribution, or importance number, of the symptoms to an analysis of depression, utilizing a neural network model. In addition, the presence of hopelessness and somatic complaints was examined, to determine their relevance to depression. Using Wave 1 data from Duke University's contribution in the Epidemiological Catchment Area (ECA) study, we created a mathematical model, a neural network, to map the relationship of nine symptoms of major depression, hopelessness and somatic complaints to the presence or absence of the formal diagnosis of depression, and performed a contribution analysis. The contribution analysis using the neural network revealed that the symptoms with the greatest impact on the occurrence of depression, or with the largest importance number for depression, were sadness, loss of interest, tiredness and sleeping trouble, in that order. The most frequently reported symptoms, though, were sadness, sleeping trouble, suicidal ideation, tiredness and poor concentration, in that order. Hopelessness and somatic symptoms were the lowest in their contribution to the diagnosis of depression. The study thus provides the hierarchy of the symptoms of depression and supports the DSM classification of major depression. © 1999 Elsevier Science Ireland Ltd. All rights reserved.

Keywords: Depression; Neural networks; Hopelessness; Somatic complaints

* Corresponding author. Tel.: +1-573-882-8008; fax: +1-573-884-5936.
E-mail address: nairj@missouri.edu (J. Nair)

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1. Introduction

The Diagnostic and Statistical Manuals (DSMs) of the American Psychiatric Association have provided a standardized classification of depression for research in recent decades. However, these classifications and descriptions of depression have been criticized (Angst et al., 1981; Van Praag, 1993) for various reasons. One criticism is that 'major depression' covers a variety of depressive syndromes (Van Praag, 1993). According to DSM-IV, a diagnosis of depression can be made with the presence of depressed mood, and/or loss of interest, and a 2-week duration of five (or more) out of nine symptoms. Thus, two individuals both having a diagnosis of major depression could have very different symptom complexes and clinical presentations. This illustrates the inherent heterogeneity of the diagnosis. Another criticism is that the relative importance of the nine individual symptoms — sadness, loss of interest (in sex), appetite change, sleeping trouble, tiredness and fatigue, psychomotor agitation and/or retardation, feelings of guilt, difficulty in concentration, and suicidal ideation (preoccupation with death) — is unclear. Moreover, there is overlap between the syndrome of major depression and dysthymic disorder.

A few studies have tried to determine the extent to which individual depressive symptoms relate to a DSM diagnosis of depression. Blazer et al. (1988) analyzed the respondents who reported depressive symptoms in the Epidemiological Catchment Area (ECA) project in the Piedmont region of North Carolina. They used a Grade of Membership classification to see whether depressive symptoms would cluster into syndromes that paralleled DSM-III diagnoses. The group reported one type that was similar to DSM-III depression, but also described four types that were not. Other syndromes were recognized as premenstrual syndrome and a mixed anxiety/depression syndrome. Most depressed people were a mix of two or more types. Thus, their study suggested a different categorization of depression items than DSM-III.

Nurcombe et al. (1989) reviewed the literature that identified the existence of both endogenous depression and neurotic (or heterogeneous) depression in adults and stated that: 'Nuclear depression in adulthood appears to be a categorically distinct entity, although probably less prevalent than usually thought. Neurotic depression, in contrast, is heterogeneous'.

In a cross-national comparison of nine countries, Weissman et al. (1996) reported the presence of insomnia and tiredness in more than 60% of depressed respondents at all sites. Concentration problems and thoughts of death were also reported at most sites. Thus, studies have been reported in the literature on the frequency of different symptoms of depression and have identified clusters of symptoms, but these studies have not commented on the relative importance of each symptom. There are no reports on the hierarchy of the symptoms of depression, from the most to the least likely to occur with the diagnosis of depression; i.e. no contribution analysis has been reported.

The purpose of the present study is to map the relationship of 11 depressive symptoms to a diagnosis of depression and to create a hierarchy of symptoms based on the chances that an individual would be diagnosed with depression if the particular symptom was present. We expect that sadness and the loss of interest in pleasure would be the most important, based on the DSM-IV criteria where at least one of the two is required to make the diagnosis of major depression. We do not know the relative importance of the other symptoms since the classification treats them as equivalent in the DSM system. We developed a neural network model to provide this additional clarification and describe a novel methodology in the article to determine the importance number of the selected symptoms.

Individual symptoms in any diagnosis in our system of classification are non-specific to the diagnosis; i.e. sleeplessness could be a symptom of depression, anxiety, or posttraumatic stress disorder. In this study, we focus exclusively on the components of the diagnosis of depression and the contribution of the individual symptoms in making the diagnosis.

Neural networks have been successfully applied in several areas including psychiatric investigation

(Reid et al., 1996; Kashani et al., 1996; Nair et al., 1996), economic analysis, pattern recognition, speech recognition and synthesis, as well as control systems (McCord-Nelson and Illingworth, 1991). A neural network is a non-linear mathematical model that applies weights to input factors to map them to output factors (Haykin, 1998; Hornik et al., 1990; Hopfield, 1982; Mistry and Nair, 1993). As stated earlier, our present research has two specific objectives: (1) to develop a neural network model to map the nine symptoms of depression and hopelessness and somatic symptoms (inputs) to the diagnosis of major depression (output); and (2) to perform a contribution analysis to determine which of these depression symptoms were most important to a diagnosis of depression by prioritizing them and assigning an importance number to them.

2. Methods

In this section we describe the sample, the neural network modeling, and the validation methodology, and we explain the novel contribution analysis procedure.

2.1. Sample

ECA surveys of mental disorders were carried out at five universities (Yale, Johns Hopkins, Washington University, Duke, and the University of California at Los Angeles) by independent research teams (Eaton et al., 1985) to estimate the prevalence of depressive disorders based on criteria derived from DSM-III. The ECA sampled over 15 000 residents living in the community at two time points between 1980 and 1984. The initial interviews were labeled Wave 1, and the follow-up interviews conducted after 1 year were labeled Wave 2. In the present study we used Wave 1 data obtained from Duke University which had 3921 respondents. The data with missing diagnoses were discarded resulting in a total of 3839 responses for the final data set. We did perform computations to ensure that the patients in the study were diagnosed correctly based on DSM-III criteria.

The relationship among the following 11 symptoms (inputs to the model) was mapped to the presence or absence of depression (output of the model) using a neural network model. The 11 symptoms included sadness, appetite change, sleeping trouble, psychomotor retardation, loss of interest in sex, tiredness, feelings of guilt, difficulty in concentration, suicidal ideation; and somatic complaint and hopelessness. Loss of interest in sex is a variable that has been used to capture the general loss of interest in the ECA data set used in this study. The last two symptoms were not included in the DSM-III diagnosis of depression but were included in this study. Hope-

Table 1
Frequency distribution of the symptoms

Symptom	Depressed respondents	Non-depressed respondents	Totals respondent	PPV (%)
Sadness	109	990	1099	9.92
Suicidal ideation	86	778	864	9.95
Somatic complaint	52	792	844	6.16
Sleeping trouble	100	637	737	13.57
Hopelessness	64	515	579	11.05
Tiredness	80	438	518	15.44
Difficulty in concentration	76	271	347	21.9
Appetite change	56	239	295	19.0
Psychomotor retardation	56	236	292	19.18
Loss of interest	50	163	213	23.47
Feelings of guilt	52	153	205	25.37

lessness was selected since it has been linked to overall psychopathology and suicide (Beck et al., 1975). We did not include details of demographics since the study focused on the individual symptoms of depression. Some of the inputs were formed by using a logical 'or' operator among similar questions (i.e. a 'yes' response to any one of the questions would result in an answer of 'yes'). For example, the sadness input was based on the logical 'or' of feeling low, empty, down in the dumps, or blue, feelings of sadness or depression, and crying a lot.

The output of the neural network model, depression, corresponds to the DSM-III diagnosis of major depressive episode. Under the DSM-III definition a person is diagnosed as depressed if he/she meets the following criteria: (i) presence of dysphoric mood and sadness; (ii) presence of at least four out of the remaining eight DSM-III symptoms; (iii) severity; (iv) no occurrence of psychotic symptoms before or independently of depression; and (v) absence of organic brain syndrome and absence of grief as the cause of depression. This definition has not changed much in the DSM-IV revision except for the inclusion of an impairment of functioning criterion.

Out of a total of 3839 respondents, 109 cases were diagnosed with depression as just stated. Table 1 shows the frequency distribution of the selected symptoms for these 109 as well as for the total.

2.2. Neural network modeling

A neural network is a mathematical model that can quantify complex relationships among the symptoms of depression and the presence or absence of depression (the output in this study) in a compact and elegant manner. As shown in Fig. 1, a neural network model can 'learn' the relationship among the symptoms and the output after it is 'trained' using a data set.

To determine which of the 11 symptoms were most important to the presence or absence of depression, a neural network model was trained and a contribution analysis performed. The multilayered neural network had the 11 selected symptoms as inputs, and the presence or absence of depression as the output. We selected 10 and five neurons, respectively, in the two hidden layers. The 3839 responses formed the training 'patterns' for the neural network. This network structure results in 261 parameters (weights) for the model, giving a pattern to parameter ratio of approximately 15, which is adequate for generalization purposes, using the training procedure described below (Haykin, 1998).

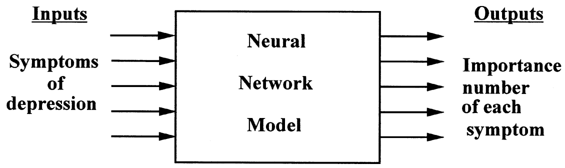

Fig. 1. Determination of importance numbers for the symptoms.

2.3. Neural network training and validation procedure

Training of the neural network was performed using back-propagation. The network was trained to minimize the mean squared error between the observed and the neural network prediction of the diagnosis. To reduce the effect of overtraining, a complexity penalty term (Finnoff et al., 1993; Weigend et al., 1990) was added to the learning function after 50 000 cycles of training. This training method allows the network to capture the relation among inputs and outputs, while keeping the complexity of the network low, thus enhancing the performance of the network for cases not seen during the training phase.

To ensure proper generalization capabilities for the neural network, a cross-validation procedure was also applied. The 3839 responses were split into two groups. A training set consisting of 80% of the data was randomly extracted from the original data set. The remaining 20% of the data were used as the validation (testing) set. The network was trained with the 80% sample while monitoring the mapping error in the validation set. No overtraining was observed during the

200 000 cycles of training, and so this was selected as the optimal number of training cycles.

This cross-validation approach, together with the selection of the network structure described above, ensures that the model learns the required relationships without losing its generalization property. After training, only two of the original 3839 responses were not learned properly by the network. The remaining 99.95% of the training data were learned adequately.

After being properly trained, a neural network acts as an expert for predictions. If a new set of inputs is presented to the network, it should be able to predict the outcome for that patient, based on the 'training' that it has received, as an expert would do. While an expert would probably have difficulty drawing inferences from a large number of symptoms, a neural network handles the complexity easily. In addition, the neural model can describe the relative importance or contribution of each input variable (i.e. symptom of depression), which may be a difficult problem for an individual expert. These trained and validated neural network weights and biases were then used to perform the contribution analysis to yield importance numbers for the symptoms.

2.4. Contribution analysis

The contribution analysis identifies the importance of the symptoms (inputs) on the presence or absence of depression by describing how much change in the model output (whether the person is depressed or not depressed) may be expected for a unit change in each input (whether the person's response to that input is yes or no). The contribution analysis considers one symptom at a time, keeping the remainder constant. This is a powerful way to change the severity of one or a group of symptoms and see the overall impact of that change on the output. Each of the 11 symptoms was perturbed from its minimum value (0) to its maximum value (1) for every patient and the output of the neural network was computed. The change in the number of predicted depressed individuals when a symptom is varied from 0 to 1 in all the patients represents the contribution of that symptom to the output, or its importance number. We can then predict the presence or absence of depression when a person's response to a question, for example, to loss of appetite, changed from 0 to 1. The methodology thus quantifies, that is, gives the importance number of each of the 11 symptoms on the outcome measure, depression.

3. Results

In our sample, the highest number of participants (depressed and non-depressed) endorsed sadness followed by (in decreasing order) suicidal ideation, somatic complaint, sleeping trouble, hopelessness, tiredness, difficulty in concentration, appetite change, psychomotor retardation, loss of interest, and feelings of guilt. Interestingly, the depressed individuals in the sample endorsed these symptoms in a different order: sadness, sleeping trouble, suicidal ideation, tiredness, difficulty in concentration, hopelessness, psychomotor retardation, appetite change, feelings of guilt, somatic complaint and loss of interest. A contribution analysis, using the neural network model, provided more detailed information about this issue, as we discuss below.

The contribution analysis provides importance numbers for each of the symptoms. Since the

Table 2
Contribution analysis results for the symptoms of depression

Symptom	Importance number	PPV (%)
Sadness	1.00	9.92
Loss of interest	0.93	23.47
Tiredness	0.90	15.44
Sleeping trouble	0.88	13.57
Difficulty in concentration	0.70	21.9
Suicidal ideation	0.61	9.95
Feelings of guilt	0.45	25.37
Appetite change	0.44	19.0
Psychomotor retardation	0.37	19.18
Hopelessness	0.28	11.05
Somatic complaint	0.00	6.16

output of the network model was binary (depressed or not), during the analysis it was assumed that the person did not have depression if the network output was ≤ 0.4, and that the person had depression if the network output was ≥ 0.6. Output values > 0.4 and < 0.6 were not counted. Table 2 presents the results of the contribution analysis for the neural network model and the normalized importance number for the symptoms based on each symptom's relationship to whether a person is depressed or not. These importance numbers were calculated by dividing the contribution of each symptom by the maximum contribution given by the sadness symptom. The normalized importance numbers have been derived from the contribution analysis using the neural network model.

Table 2 shows that sadness has a normalized importance number of 1 while somatic complaints has a normalized importance number of 0. A symptom having a higher importance number has a greater effect on the outcome. The neural network determined that sadness was the primary symptom in diagnosing depression. A total of 109 depressed individuals endorsed sadness while 990 non-depressed persons did so (Table 1). Only 50 depressed individuals admitted to having loss of interest, but, despite this primary symptom not occurring more frequently in the raw data set, the neural network contribution analysis found loss of interest to be the second most important symptom in determining the presence of depression in a patient (Tables 1 and 2). There was a little correlation ($\rho = 0.10$, $P = 0.77$) between the neural network ranking of the selected symptoms and their frequency distribution in the data set.

Compared to the Positive Predictive Value (Table 2) technique, the contribution hierarchy is different in emphasizing the additional dimension provided by the neural network technique to the diagnosis.

The neural network analysis grouped sadness, loss of interest, tiredness and sleeping trouble as the four major symptoms of depression, in that order. A group of symptoms of secondary importance was formed by difficulty in concentration, suicidal ideation, feelings of guilt, and appetite change. Finally, a third group was identified associated with the symptoms of psychomotor retardation, hopelessness and somatic complaint.

3.1. Logistic regression analysis

The 11 variables were entered into a logistic regression equation with depression as the dependent variable. When a backwards elimination procedure was used, three variables, somatic complaints, hopelessness, and psychomotor retardation, were eliminated. These three variables had the lowest values in the contribution analysis, and the chi-square values of each of their parameter estimates all had P values > 0.10. Table 3 shows the maximum likelihood estimates for the remaining eight variables, along with their chi square values and respective P values. The remaining eight variables had P values < 0.0001. The order of the relative magnitudes of these estimates differed somewhat from the order of the magnitudes of the importance numbers from the neural network analysis. For these remaining eight variables, the rank correlation of the parameter regression estimates with the importance number was 0.62, $P > 0.10$. Thus, there remain some differences between the relative contribution of the variables as identified by the non-linear neural network and by the regression analysis. Loss of interest ranked sixth in the logistic analysis but second in the contribution analysis; sleeping trouble ranked first in the logistic analysis but fourth in the contribution analysis. All other ranks either differed by one or were the same.

Table 3
Logistic regression maximum likelihood estimates

Symptom	Chi-square	P	Estimate
Intercept	200.23	0.0001	
Sadness	16.41	0.0001	−0.44
Appetite change	17.84	0.0001	−0.17
Sleeping trouble	34.39	0.0001	−0.50
Tiredness	30.74	0.0001	−0.29
Loss of interest	23.58	0.0001	−0.18
Feelings of guilt	18.85	0.0001	−0.15
Difficulty in concentration	34.62	0.0001	−0.25
Suicidal ideation	14.68	0.0001	−0.27

4. Discussion

Clinicians diagnose major depression frequently on the basis of expression of sadness and our analysis indicates that in adults sadness was the most important component, followed by loss of interest, tiredness, sleeping trouble, difficulty in concentration, suicidal ideation, feelings of guilt, appetite change, and psychomotor retardation. This supports the present concept of the two cardinal symptoms of depression in the DSM system, although our analysis suggests that the first four are of prime importance. Also, since sad mood and loss of interest are the primary symptoms for a diagnosis of depression, one would expect the contribution analysis to determine that these two were more important relative to the others, which it did.

Clinicians rightly consider sadness as an important symptom of depression. Our results with the ECA adults indicate that tiredness and sleeping trouble are also important components in the diagnosis. Thus the primary physicians (internists, family practitioners, etc.) who come across patients with fatigue and sleeping trouble may question the person further about other depressive symptoms. Table 1 indicates that approximately one in seven individuals who complain of tiredness and sleeping trouble may be depressed. Tiredness is the third most important symptom of depression followed by sleeping trouble.

Suicidal ideation and preoccupation with death are extremely worrisome symptoms, and some practitioners may believe that all suicidal persons are depressed. Our results show that this symptom, although part of the depressive cluster, is number six in the ranking of hierarchy of depressive symptoms despite its dramatic presentation. According to Table 1, out of 864 individuals with suicidal ideation, 86 were depressed, suggesting that only about 1 in 10 persons reporting suicidal thoughts met DSM-III criteria for a diagnosis of major depression. However, the seriousness and the frequency of suicidal ideation are not mentioned. This finding is consistent with the common observation of suicidal intent in other diagnoses such as anti-social personality disorder, schizophrenia and bipolar disorder. Although suicidal ideation is very important and should be taken seriously, having suicidal thoughts, obviously, is not equivalent to having depression. As our data indicate, other symptoms such as sleeping trouble and tiredness are much more representative of depression than suicidal ideation.

Weissman et al. (1996), in a cross-national comparison of nine countries, reported that sleeping trouble and tiredness were found in more than 60% of the depressed respondents at all sites. The respondants also described frequent loss of concentration and thoughts of death. These results and our contribution analysis results support each other. Our study confirms that tiredness, sleeping trouble, difficulty in concentration and suicidal ideation are important symptoms of depression, in addition to the two cardinal symptoms.

The strength of using neural networks to find the importance number of symptoms in making the diagnosis of depression is demonstrated by the marked difference between the frequency distribution of a particular symptom and its calculated importance number. Sadness, sleeping trouble, suicidal ideation, poor concentration, psychomotor retardation, appetite change and loss of interest are the symptoms in order of decreasing frequency. Loss of interest was the second most important symptom even though the number of respondants reporting this symptom was less than half of those endorsing sadness. Tiredness was next, followed by sleeping trouble. Hence, the importance number gives additional information to reports of frequency of symptoms. It gives us a hierarchy of the components of depression.

Logistic regression also produced a hierarchy, but the hierarchy of variables as identified by logistic regression correlated only modestly with the hierarchy of variables as identified by neural network techniques. The greatest difference in ranks of the symptoms between the neural network analysis and regression was in loss of interest, which the neural network analysis ranked second but the regression analysis ranked sixth. Since loss of interest (along with sadness) is required for depression, we are more inclined to favor the neural network analysis rather than the logistic regression, if we had to choose.

Logistic regression is a statistical method which assumes that a vector of explanatory variables can be modeled by a logistic function. The model is satisfactory to the degree that the variables fit the model. Neural network analysis is a mathematical model which makes no demands upon the functional characteristics of the variables. The differences we see in the results of the two methods arise from the differing ways of analyzing the same data.

Hopelessness is not one of the components of major depression, but it is a component of dysthymic disorder in addition to sleep and appetite disturbance, low energy and self-esteem, and poor concentration. It is also linked to overall adolescent psychopathology. Our analysis shows that hopelessness and somatic complaints were the least important symptoms in the diagnosis of depression in adults. This finding supports the DSM-IV classification for major depression which excludes these symptoms from the cluster. The regression analysis clearly eliminated hopelessness, somatic complaints, and psychomotor retardation as significant predictors of depression.

These results will be applicable to populations with similar background and makeup. It is possible that since depression is a culture-bound syndrome, other cultures would show an entirely different picture if a similar study were performed. Our conclusions are based on responses in a particular area of this country, in a Western industrialized society. These results are based on a general adult population, and their utility is limited to this age group. A similar study might have different results if performed in children and adolescents.

The results of the neural network application to the diagnostic classification demonstrate that expression of sadness, loss of interest, tiredness, and sleeping trouble are the top four important symptoms in the diagnosis of depression in adults. However, it adds to current knowledge by also giving special importance to tiredness and sleeping trouble. This supports the present system of diagnosis. A significant finding using neural networks was also that the most important symptoms are not necessarily the most frequently observed. The present study also provides a list showing the hierarchy of depressive symptoms among the symptom cluster. The model would predict that clinicians who affected the important symptoms would have the greatest impact on reducing depression. The logistic regression would identify the top four as sleeping trouble, sadness, tiredness, and suicidal ideation. Its omission of loss of interest and addition of suicide ideation seems less in harmony with our clinical experience. The use of neural networks in this study is only one application of the model to clinical depression. As demonstrated in our earlier publication (Kashani et al., 1996), this method can be used not only in mood disorders but also for other diagnostic categories in both adults and children.

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