

Overcoming the Limitations of the Descriptive and Categorical Approaches in Psychiatric Diagnosis: A Proposal Based on Bayesian Networks



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SUMMARY

Efforts to overcome the problems of descriptive and categorical approaches have not yielded results. In the present article, psychiatric diagnosis using Bayesian networks is proposed. Instead of a yes/no decision, Bayesian networks give the probability of diagnostic category inclusion, thereby yielding both a graded, i.e., dimensional diagnosis, and a value of the certainty of the diagnosis. With the use of Bayesian networks in the diagnosis of mental disorders, information about etiology, associated features, treatment outcome, and laboratory results may be used in addition to clinical signs and symptoms, with each of these factors contributing proportionally to their own specificity and sensitivity. Furthermore, a diagnosis (albeit one with a lower probability) can be made even with incomplete, uncertain, or partially erroneous information, and patients whose symptoms are below the diagnostic threshold can be evaluated. Lastly, there is no need of NOS or “unspecified” categories, and comorbid disorders become different dimensions of the diagnostic evaluation.

Bayesian diagnoses allow the preservation of current categories and assessment methods, and may be used concurrently with criteria-based diagnoses. Users need not put in extra effort except to collect more comprehensive information. Unlike the Research Domain Criteria (RDoC) project, the Bayesian approach neither increases the diagnostic validity of existing categories nor explains the pathophysiological mechanisms of mental disorders. It, however, can be readily integrated to present classification systems. Therefore, the Bayesian approach may be an intermediate phase between criteria-based diagnosis and the RDoC ideal.

Keywords: Bayesian networks, Bayesian method, mental disorders, diagnosis, classification, diagnostic techniques and procedures, DSM

INTRODUCTION

The descriptive approach has been and still is the dominant approach in the diagnosis of mental disorders since the neo-Kraepelinian revolution in 1980. Even though standard diagnostic criteria introduced in the third edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM-III) solved the problem of reliability, the DSM and ICD (International Classification of Diseases) systems have been criticized for not considering etiology and laboratory investigations in making diagnoses (McHugh 2005, Luyten and Blatt 2007). Although the results of many biochemical tests, imaging techniques, and psychological tests on clinical samples have been found to differ from normal subjects in certain diagnostic groups,

none of them has been found to have sufficient sensitivity and/or specificity to become a diagnostic criterion (Kapur et al. 2012). Psychiatric diagnosis thus seems trapped in the descriptive approach and DSM remains a classification of syndromes rather than a classification of disorders.

Another criticism of psychiatric diagnosis concerns the categorical approach. The DSM and ICD consider mental disorders as discrete categories. However, problems stemming from the categorical approach have become more conspicuous with time, and the idea that this approach should be revised has been expressed more frequently (Clark et al. 1995, Widiger and Samuel 2005, Krueger and Bezdjian 2009). Many authors have maintained that these problems can be overcome only by the adoption of a dimensional classification

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(Helzer et al. 2006, Widiger and Gore 2011, Mellsop et al. 2007). Nevertheless, in spite of these efforts, the development of a dimensional model that can retain the advantages of categories while minimizing their drawbacks, and that can be accepted by the majority of users proved difficult (Verheul 2012, Kecmanovic 2012). The final evidence for this is the DSM-5. In spite of more than a decade of work, the DSM-5 Task Force had still not been able to develop the classification of mental disorders on a dimensional basis. This is stated in the introduction of the DSM-5, as follows: “*Despite the problem posed by categorical diagnoses, the DSM-5 Task Force recognized that it is premature scientifically to propose alternative definitions for most disorders*” (American Psychiatric Association 2013).

Thus, in this article, a diagnosis of mental disorders based on Bayesian networks (BNs) is proposed. This model allows going beyond the descriptive approach and the using of information concerning etiology, associated features, and laboratory tests in the diagnostic process. Moreover, since this method yields a dimensional diagnosis (a probability value), it is not only free of the disadvantages of the categorical approach, but also enables the expressing of the certainty of our diagnosis. Furthermore, this can be accomplished without disrupting the existing system.

In the first part of the paper, problems arising from the categorical approach and obstacles to the development of a dimensional diagnostic system are summarized. I will also consider the “illusion of certainty,” which is an important drawback of criteria-based diagnoses and which has not been addressed sufficiently. In the second part, I present BNs, discuss the benefits and defects of such a diagnostic method when applied to mental disorders, and propose a program to implement a Bayesian diagnostic system for psychiatry.

Problems Related to the Categorical Approach

The literature on psychiatry addressing the drawbacks of the categorical approach (Clark et al. 1995, Widiger and Samuel 2005, Kraemer 2007, Krueger and Bezdjian 2009, Widiger and Gore 2011) is extensive, and reviewing it is beyond the scope of this paper. Nevertheless, in order to facilitate the discussion on the advantages of BNs, I shall shortly summarize these problems.

- Diagnostic categories largely overlap and their borders are unclear. The most important sign of this are high rates of NOS diagnoses and excessive diagnostic co-occurrence.
- In criteria-based diagnosis, a patient is included into a category only when s/he has enough symptoms to reach or exceed the diagnostic threshold of that category. Patients whose symptom count is below the threshold do not receive much attention and are excluded from the studies.

- All patients who exceed the diagnostic threshold are placed in the same category. However, the number of symptoms (the severity of the disorder) in these patients is not considered, thereby ignoring any differences among them.
- The DSM does not consider the sensitivity, specificity, and predictive power of symptoms. With some exceptions, all diagnostic criteria of a category are ascribed equal importance (Clark et al. 1995). However, the diagnostic significance of each symptom differs. For instance, the DSM-5 attaches equal importance to fatigue and delusions of guilt as criteria of major depressive disorder. However, fatigue occurs in many other disorders, i.e., has very low specificity for depression, while delusional guilt is highly specific to depression.
- With few exceptions, the DSM does not use etiological information in diagnosis. While it is true that the etiology of most disorders remains unknown, many factors that lead to susceptibility and increase the likelihood of having the disorder have been identified. For example, the presence of bipolar disorder in one patient’s family increases the probability of that patient having bipolar disorder. However, this increase in probability cannot be employed in the present criteria system.
- The DSM does not take advantage of information about treatment outcomes in making diagnosis. For example, knowing that a patient has benefited from antipsychotic medication increases the probability of a psychotic disorder in that patient.
- Another important problem stemming from the categorical approach is the illusion of certainty, which I discuss in more depth below.

The Certainty Illusion. The DSM system implicitly assumes that criteria-based diagnoses are certain. It also presupposes that we can determine the presence or absence of symptoms definitely. Users are forced to say either “definitely present” or “definitely unmet” for a symptom or criterion. However, in practice, we cannot be absolutely certain of the presence or absence of a symptom. To quote Elstein (1999), “[r]eaching a diagnosis can be conceptualized as a process of reasoning about uncertainty ...” In practice, psychiatrists are well aware of this fact and often state their degree of certainty (“*I think this patient has a 70% of probability of having anorexia nervosa*”) when discussing their diagnostic decisions. This uncertainty is undesirable, but such is the nature of medicine and of psychiatry. Many errors decrease the certainty of our diagnoses. The sources of these errors are

- a) Abstract and uncertain data. Psychopathological symptoms are abstract phenomena and depend upon the subjective judgment of the psychiatrist, which leads to erroneous

and unreliable diagnoses (Beauchaine 2007). It is difficult to ascertain whether they have reached the threshold of being pathological. This imprecision is due to the lack of direct relationship between observed symptoms and their underlying (but mostly unknown) pathophysiological mechanisms (Sorias 2012). Meehl (1995) reported that psychiatric symptoms are liable to erroneous interpretation as indicators of the underlying disease. According to Beauchaine (2007), *“Behavioral symptoms are far removed from the genetic, neural, and physiological substrates of psychopathology... and are therefore characterized by significant measurement error when used as indicators of these substrates.”*

b) Incomplete data. All the information required to make a diagnosis cannot be obtained much of the time. Making diagnoses or clinical decisions with incomplete data is the rule rather than the exception. In artificial intelligence, the necessity to make decisions with incomplete information is termed “ignorance” (Russel and Norvig 1995, p.416).

c) Human error. Observation and interpretation errors by the clinician lower the certainty of the diagnosis.

Although they may be erroneous, criteria-based diagnoses are presented as absolutely certain. For instance, if a clinician is only 80% certain that some criterion has been met, s/he considers it met most of the time even though s/he knows that it is not certain. Although we know that some degree of error enters our diagnostic decisions, we are unable to express or quantify this error. Take, for example, that we are only 80% certain that a patient has schizophrenia. In practice, we consider this patient schizophrenic and treat accordingly. However, if 100 such patients are included into a schizophrenia study, a large error that may markedly influence the results appears. If the mean value of the diagnostic certainty of the group is 0.80, according to the law of large numbers, approximately 20 of these patients do not have schizophrenia. We thus cannot know which patients belong to this subgroup and cannot reduce this number by taking a larger study group.

Many authors have suggested that these drawbacks can be overcome by adopting a dimensional classification. The dimensional approach uses a graded evaluation and considers mental disorders not as discrete categories but as a continuous dimension, and places each patient at a certain point in this continuum (Widiger and Samuel 2005). However, due to some practical and theoretical reasons, the dimensional approach could not be realized so far. These reasons are summarized below.

Advantages of the Categorical Approach and Barriers to a Dimensional Classification

- Diagnostic categories are easy to use and preferred by humans. They provide the cognitive advantages described in the theory of mental categories (Rosch 1978). Separating

phenomena into different categories facilitates their recognition, recording, and recall. Diagnostic categories also ease professional communication (Kamphuis and Noordhof, 2009).

- The categories are consistent with the rest of medicine. The categorical approach is an integral part of the medical model (Widiger and Gore 2011).
- Clinicians are familiar with this system. The diagnostic categories we currently use are old typologies for which a wealth of knowledge has been collected by different psychology and psychiatry schools. Abandoning mental disorder categories will also mean abandoning all this knowledge and old research findings.
- A dimensional classification should be backward compatible. When a new system is developed to replace a previous one, this new system should be able to perform all the functions of the previous one plus the new functions that are specific to it. A dimensional system should not require us to redo all the investigations made according to categorical diagnoses and discard all former patient files and reports (Mullins-Sweatt et al. 2012).
- A dimensional model should be easy to use and have clinical utility (First 2005, Kecmanovic 2012).
- No matter how good a dimensional/graded evaluation is, it is inadequate by itself. In day-to-day clinical practice, we have to make many categorical decisions such as whether the patient should undergo ECT or is responsible for the offense s/he committed. These are questions that can only be answered as yes or no, i.e., questions that require categorical answers (Kraemer et al. 2004, Helzer et al. 2006, Hudziak et al. 2007).

Bayesian Networks and Bayesian Diagnosis

A Bayesian network (Bayesian belief network or Belief network; BN) is an artificial intelligence technique based on probability theory that emerged in the 80s. This technique is used to model causal relationships and perform probabilistic reasoning under uncertainty (Charniak 1991, Russel and Norvig 1995). BNs represent the relationships between the variables of the modeled problem with conditional probabilities, making use of a graphical user interface. Most importantly, they yield sensible results even with incomplete, vague, and partially correct data (Nikovski 2000). When the model is run, it presents the result as a probability value. Thus, it can tell how certain is the answer to our question *in view of the existing data*. They are particularly useful where a definite conclusion cannot be reached because of the nature of the problem or insufficient data. They are used in various areas such as statistics, image processing, decision support, natural language understanding, and troubleshooting, but they are most useful in medical diagnosis (Lucas 2001).

Bayesian networks are based on Bayes' theorem developed by the 18th century English mathematician Thomas Bayes. This theorem (with the names of the variables adapted to the medical domain) is stated by the following formula:

$$P(d | s) = \frac{P(s | d) P(d)}{P(s)}$$

In the above formula, d denotes disorder and s denotes symptom.

$P(d | s)$ is a conditional probability and indicates the probability of the patient having disorder d when symptom s is observed (positive predictive value).

$P(s | d)$ is the probability of observing symptom s in a patient with disorder d (sensitivity).

$P(d)$ is the unconditional or prior probability of disorder d . That is, the probability of d in some person we have not seen yet.

$P(s)$ is the unconditional probability of s .

Bayesian networks no doubt are beyond this simple formula, consisting of a group of techniques implemented by many algorithms. A BN consists of a set of interconnected nodes where the nodes represent variables and the connecting arcs represent the causal relations among the variables. The node where the arrow starts is called the "parent" and the one where it ends, "child." The quantitative relationships between nodes

are represented with probability values in conditional probability tables (CPT) of the child nodes.

To explain the subject, I will present a very simple BN for diagnosing schizophrenia as an example. I must emphasize that this is not a realistic model, but only a tool to explain the functioning of the network. In artificial intelligence, such oversimplified models are termed "toy models" (Russel and Norvig 1995). They can be likened to model airplanes. A model airplane does not make us fly, but may help us understand the mechanisms of flight.

Figure 1 shows our model network. This network has only eight nodes. However, a realistic network to diagnose schizophrenia will probably have a far higher number of variables. When the network is run, the **Schizophrenia** node in the middle shows the probability of the patient having schizophrenia (the names of nodes are written **with this type-face**). In the upper row are three of the factors believed to play a role in the etiology of schizophrenia. These are **Born in Winter**, **Family History of Schizophrenia**, and (premorbid) **Schizotypal Personality Disorder**. The relative importance of these factors in the etiology of schizophrenia differ, which is demonstrated in their respective conditional probability tables.

In the lower row we see the nodes **Delusions**, **Inappropriate Affect**, and **Course**, and in the right, the node **Response to Antipsychotics**. Among these

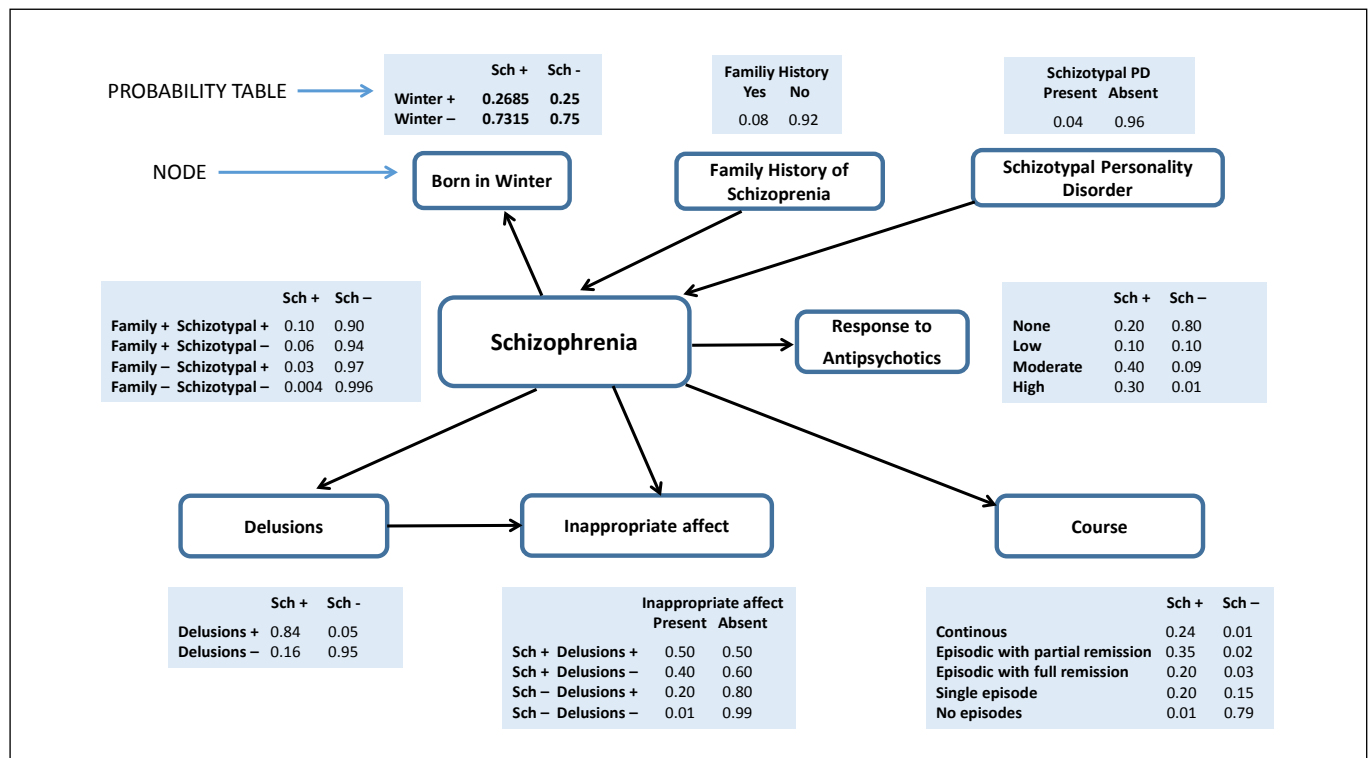


Figure 1. A model Bayesian network to diagnose schizophrenia.

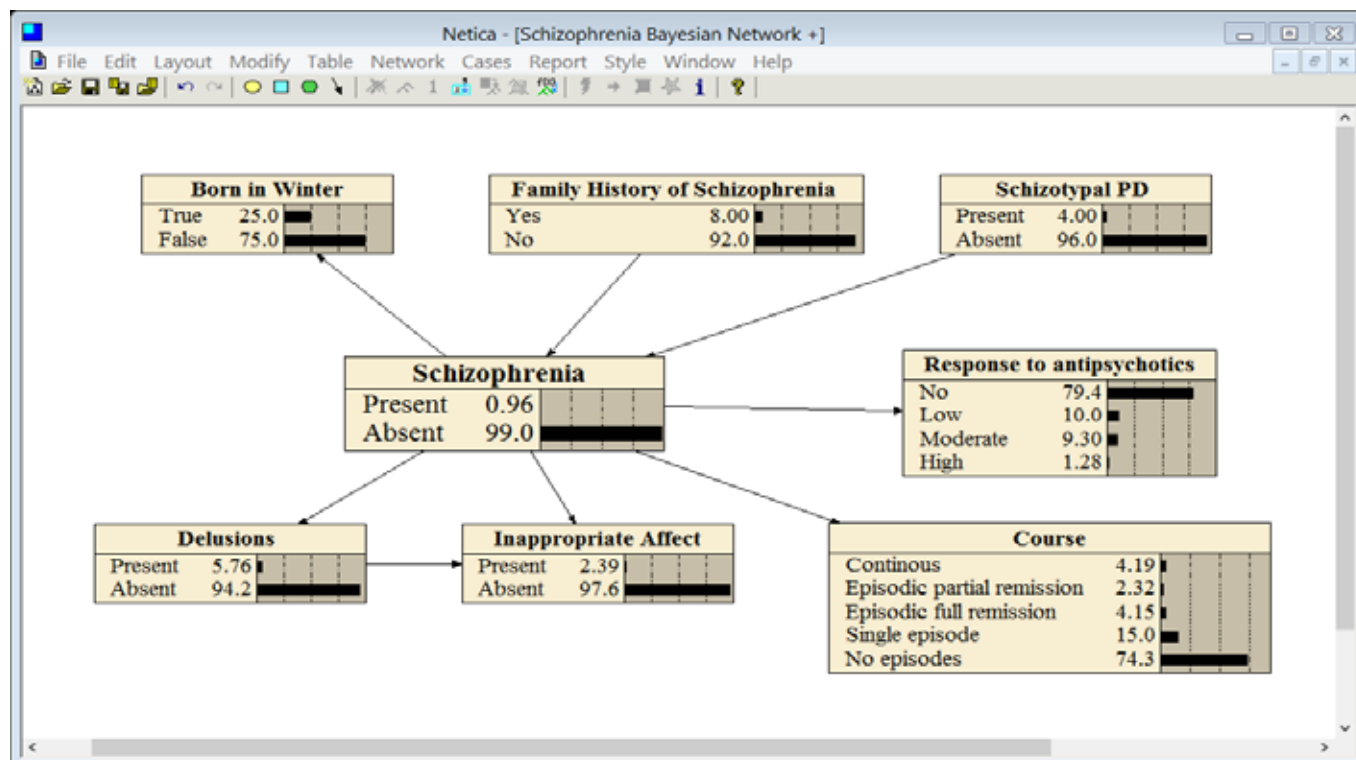


Figure 2. The user interface of a program implementing our model network. The program used is Norsys Software's Netica 5.12. Since no data had been entered, all the nodes are in the *unknown* state.

variables, only **Delusions** is a diagnostic criterion in the DSM-5; **Inappropriate Affect** is a clinical symptom but not a criterion. **Course** and **Response to Antipsychotics** are neither symptoms nor etiological factors, but since they affect the probability of a patient having schizophrenia, they can be used here. The only factor we need to know is the conditional probabilities indicating the relations between the variables.

In Figure 1, the conditional probability table of each node is placed next to it; the probability values are my estimations. The meaning of the figures seen in the CPT of **Delusions** are as follows: 0.84 is the probability of delusions in a schizophrenic patient (sensitivity), 0.16 is the probability of not observing delusions in a schizophrenic patient (false negative rate), 0.05 is the probability of observing delusions in a person without schizophrenia (false positive rate), and 0.95 is the probability of not observing delusions in a person without schizophrenia (specificity).

Similarly, the number 0.2685 in the node **Born in Winter** indicates the probability of a schizophrenic patient being born in winter and the figure 0.25 indicates the probability of someone without schizophrenia being born in winter.

Since the node **Family History of Schizophrenia** has no parent nodes, only its unconditional probability is stated: 0.08 denotes the probability of a random individual having a

family history of schizophrenia. Similarly, the unconditional probability of **Schizotypal Personality Disorder** is given as 0.04. The conditional probabilities of the other nodes are shown in their respective tables.

The user interface of the computer program implementing our model network is shown in Figure 2. The software used is Norsys Software's Netica 5.12. When a Bayesian network is started and before any data is entered, all the nodes are in the *unknown* state. It can be seen that the prior probability of **Schizophrenia** is given as 0.0096 that of **Delusions** as 0.0576, and the probability that a random individual will benefit moderately from antipsychotic treatment is 0.0930 (the program I use shows probabilities in percentages).

We can now start to input our findings. Let us assume that we have a patient about whom we could obtain very little information. All we know is that she has delusions, a family history of schizophrenia, and was born in February. We can enter this data via the user interface of our network. Figure 3 shows our network's state after the information above is entered. As seen in the Figure, when the nodes **Delusions**, **Family History of Schizophrenia**, and **Born in winter** are set to *true* or *present*, our network gives the probability of **Schizophrenia** as 0.542. With every datum entered, Bayesian algorithms simultaneously update all nodes. Not only did the probability of **Schizophrenia** increase to 0.542, but the expected probabilities of the variables of

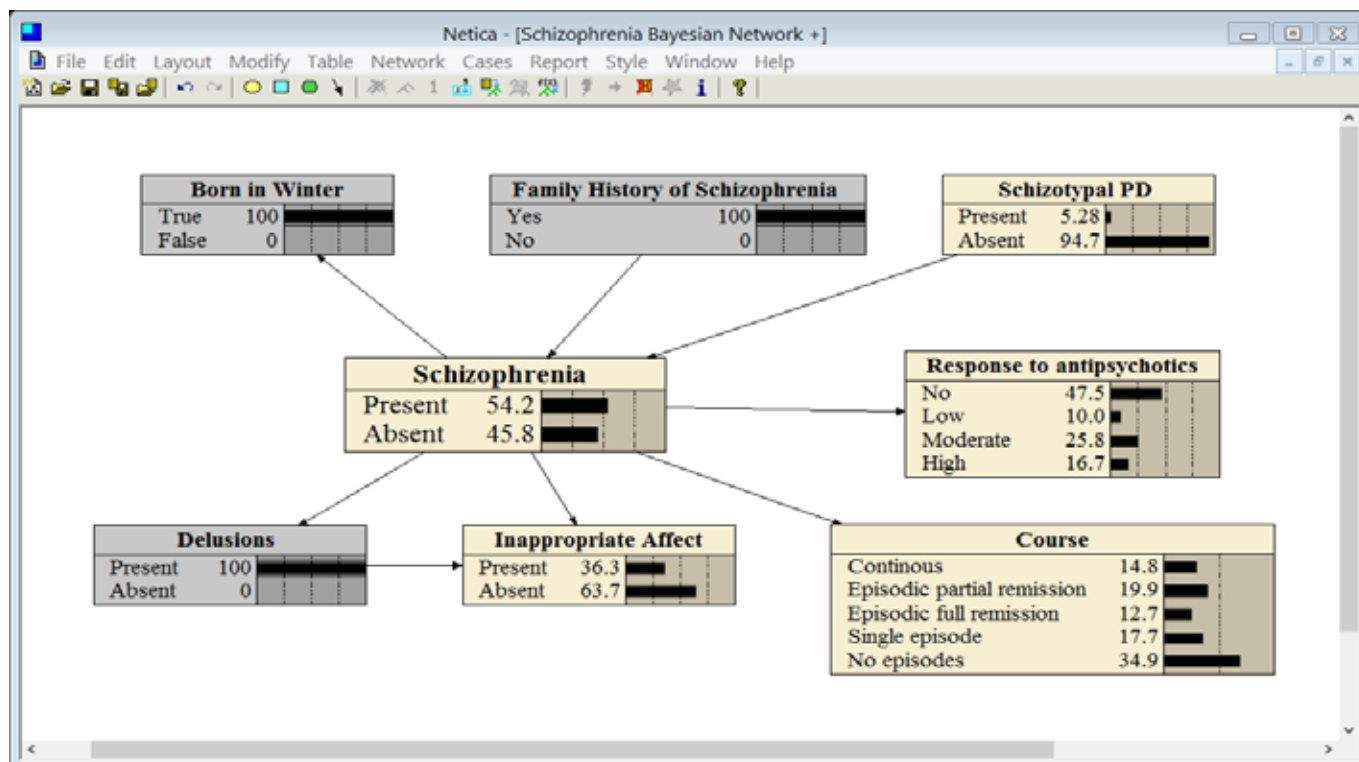


Figure 3. The nodes, **Born in Winter**, **Family History of Schizophrenia**, and **Delusions** have been set to *True*, *Yes*, and *Present*, respectively. Now our model network gives the probability of having **Schizophrenia** as 0.542. All the other nodes' expected probabilities were also changed, e.g., the expected probability of premorbid **Schizotypal PD** rose to 0.0528 and that of **Inappropriate Affect** to 0.363.

which we do not yet have information were also changed. We can observe that the probability that our patient will benefit moderately from antipsychotic treatment has increased from 0.093 to 0.258 and that the probability of her having inappropriate affect increased from 0.0239 to 0.363.

Properties of Bayesian Networks

As can be seen, BNs express diagnosis as a probability of the patient having that disorder or belonging to that diagnostic category. In other words, BNs tell us how certain the diagnosis is. Knowing the probability or certainty of a diagnosis has two important advantages. First, as a numerical value, it endows diagnosis with a dimensional attribute. Second, it protects us from the illusion of certainty imposed by criteria-based diagnoses.

BNs function perfectly with incomplete data and give the probability of the concerned diagnosis in view of available data. In our hypothetical example, as we entered merely three pieces of information, the probability of the patient having schizophrenia is only 0.542. The more information we enter as *present* or *true*, the higher the probability. Conversely, information entered as *false* or *absent* decreases the probability of the patient's having that disorder. When all variables are in the *unknown* position, the probability of having that disorder is called *prior probability* (or *pretest probability*). This value is approximately the prevalence of that disorder in individuals

chosen randomly from the general population. On the other hand, in an outpatient setting, the prior probability of a disorder is the ratio of patients having said disorder among all patients examined in that clinic.

In a BN, a finding may be in one of five different states: *present*, *absent*, *partially present*, *present with a certain probability*, and *unknown*. However, in criteria-based diagnosis, a criterion may be either *present* or *absent*. In the DSM, any symptom that we do not have information about is considered *absent*. BNs, on the other hand, distinguish between "patient does not have the symptom" and "we do not have any information about the symptom." In a BN, while leaving a finding *unknown* does not change the prior probability of the disorder, stating that it is *absent* or *false* decreases it.

Variables in a BN may take discrete or continuous values. For instance, **Born in Winter** is a categorical variable that can be either *true* or *false*. However, **Response to Antipsychotics** is a graded concept and takes one of four values: *None*, *Low*, *Moderate*, and *High*. Similarly, symptoms such as impairment of functioning or decreased sleep that are coded as *present* or *absent* in the DSM can be defined as nodes that take ordinal values in a BN. Numerical variables such as age and level of intelligence can be directly entered as numbers. This property gives a dimensional quality to the *symptoms* as well.

BNs allow entering findings whose presence we are not certain about or which involve measurement errors. This can be done by stating a probability value expressing this uncertainty or error. For example, due to the unreliability of the information we received, if we are only 50% certain of the presence of another schizophrenia case in the patient's family, then the probability that this finding is *present* may be reported as 0.50. This increases the probability of the disorder less than entering it as *certainly present* but more than leaving it as *unknown*.

Each characteristic that has a statistical relationship with and may influence the likelihood of a patient receiving a certain diagnosis can be made a node in a Bayesian network. Etiological factors, associated features, and laboratory data that cannot be used in criteria-based diagnosis because of their low sensitivity and/or specificity may be used in this context.

Symptoms with low specificity and sensitivity cannot be of much use by themselves, but when combined with the help of a technique called Bayesian updating, may considerably change the probability of having that disorder. For example, being born in winter plays a much less important role in the etiology of schizophrenia than, for example, genetic factors. In a BN, this factor's contribution to the probability of schizophrenia is proportional to its etiological importance. It is known that most psychiatric disorders have a multifactorial etiology and are due to the cumulative effect of multiple factors. Bayesian networks model this multifactorial etiology and calculate the probability of a disorder by taking into account the relative importance of each factor.

A factor thought to be etiological does not necessarily have to play an actual role in the etiology of that disorder. A significant, even small, relationship between an external factor and a diagnostic category and the demonstration of that relationship in the conditional probability tables suffices. This relation does not have to be explained. For example, whether being born in winter is a factor in the etiology of schizophrenia is debatable. Nevertheless, since many studies have identified a weak but significant relationship between it and schizophrenia, it may be incorporated into a network for diagnosing schizophrenia. We do not have to know its mechanism in the development of schizophrenia.

BNs also enable the modeling of relationships between data (De la Fuente et al. 2011). For example, hallucinations mostly occur concurrently with delusions, presumably because both are produced by the same pathological process. A patient with delusions has a higher probability of having hallucinations compared to a patient without delusions. Similarly, in patients with depression, the probability of suicidal ideas is higher when feelings of guilt are also present. In other words, for symptoms produced by the same disease process, one plus one does not equal two. However, criteria-based systems do not consider the dependency between symptoms. In the DSM-5, delusions and hallucinations are two completely independent

symptoms. In major depressive episode, excessive guilt and suicidal ideas are two *criteria* independent of each other. In our model network, as the presence of **Delusions** increases the probability of **Inappropriate Affect**, there is a relationship (arrow) between these two nodes. In Figure 1, the degree of this relationship is demonstrated in the conditional probability table of **Inappropriate Affect**. We can see in the table that the probability of **Inappropriate Affect** increases in the presence of **Delusions** and decreases in their absence.

The Advantages of Bayesian Diagnosis in Psychiatry

Thus, BNs have important advantages over criteria-based descriptive/categorical approaches. Incorporation of this method into diagnostic systems such as the DSM and ICD could solve most of the disadvantages of criteria-based and categorical approaches:

1. Dimensional Diagnosis.

"Every categorical diagnosis can be made dimensional by using symptom counts, symptom duration, symptom severity, degree of impairment, *certainty of diagnosis* . . . and many more such strategies even without deviating from the contents of current DSM categorical diagnoses. *Thus the issue is not whether a dimensional diagnosis can be added to each categorical diagnosis, it is merely how best to do that for each*" (Kraemer 2007, emphasis added).

Bayesian networks make a graded evaluation, thus yielding a dimensional diagnosis. Moreover, this is not an ordinary rating score but a probability value, which is much more suitable for statistics (Helzer et al. 2007, Kraemer 2007). Thanks to BNs, we can obtain a figure denoting the certainty of diagnosis without the certainty illusion of criteria-based diagnoses. Psychiatrists will now be more aware of the fact that their diagnoses are not absolutely certain.

2. More than Clinical Signs. Perhaps the greatest gain is that, for the first time, an opportunity arises in psychiatric diagnosis for going beyond the descriptive approach. In addition to clinical signs and symptoms, information about etiology, associated features, laboratory findings, and treatment outcome can be used in diagnosis. In the DSM, only findings with high sensitivity and/or specificity could be made diagnostic criteria and, owing to the rigidity of criteria-based diagnosis, symptoms have been given equal weight in most of the categories. However, in the Bayesian approach, each feature contributes in proportion to its own specificity and sensitivity. Fatigue and delusions of guilt are no longer of equal importance in the diagnosis of major depressive episode. This is also true for the other factors used in making a diagnosis. The presence of a close relative with schizophrenia increases the probability of schizophrenia much more than being born in winter does.

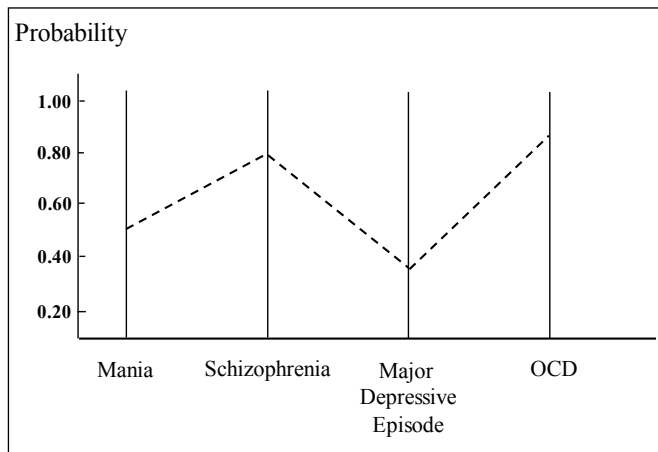


Figure 4. Bayesian diagnostic evaluation of a hypothetical case. The four diagnostic categories shown in the figure have been found to have a probability higher than a predetermined threshold and the results are presented in a format similar to the MMPI profile. In this way categories may be interpreted as various dimensions of the clinical picture.

3. No NOS Diagnoses. One of the most important complaints about the categorical approach is the high number of patients falling into the “unspecified” (formerly NOS) categories (Clark et al. 1995). Since a Bayesian diagnosis states to what extent a patient belongs to a category, the concept of “patient belonging to no category” will be obsolete.

4. No Pointless Multiple Diagnoses. The Bayesian method would also solve the problem of excessive comorbidity. As this method is applied to each relevant category, the categories become different dimensions of our diagnostic evaluation. Here is another oversimplified example: assume that we evaluate a patient using BNs and find probability values over 0.20 (the hypothetical threshold) in the categories of manic episode, schizophrenia, major depressive episode, and OCD. These results can be presented in a format similar to the MMPI profile (Figure 4). As seen in the figure, categories may be interpreted as various dimensions of the clinical picture.

5. Backward Compatibility. Bayesian diagnoses are completely compatible with the existing system. We do not have to abandon or change existing categories and can continue to use them in the same manner. We still collect the same information from patients. The clinical examination does not change and clinicians do not need to be retrained. We can make both a criteria-based and Bayesian diagnosis with the same information. A Bayesian diagnosis can easily be transformed into a classical one, meaning that Bayesian and criteria-based evaluations can be used together. Helzer et al. (2006) stressed that “[while implementing a dimensional method] it is vital that we also preserve a solid bridge to the categorical taxonomy.” According to the authors, the best option is to preserve existing categories and add a dimensional component to them, which is what the Bayesian approach does.

6. Partial Diagnosis with Incomplete Information. BNs are able to make a diagnostic evaluation (albeit one with lower

probability) with incomplete information. A categorical diagnosis is often deferred due to inadequate data; however, given that treatment cannot be deferred, the benefit of knowing the most probable diagnosis should not be underestimated (Elstein 1999). Likewise, findings that are dubious or that include errors can be used in the diagnostic process provided that the degree of certainty or size of the error is stated. For example, if a patient we suspect to have delusions denies them, we can state that “*delusions are present with 0.30 probability*,” which is much more accurate than recording them as *absent*.

7. Comprehensive Evaluation. While structured interviews on DSM diagnoses focus only on diagnostic criteria, the Bayesian method calls for the collection of much more comprehensive information. One of the criticisms directed towards the DSM is that it neglects a careful clinical evaluation targeted at individual problems and social context, and distances psychiatry from the humanistic approach it should possess (Andreasen 2007). The Bayesian approach can change this attitude because it requires collecting as much data that are statistically related to a diagnostic category as possible.

8. Easy to Use and Acceptable. The Bayesian approach preserves the existing categories and diagnostic evaluation methods. It does not place any extra burden on clinicians and requires simply the traditional examination of patients and entering data into a computer. In addition programs implementing Bayesian diagnosis would probably be found on the Web, freeing the user from issues such as program maintenance. Moreover, the method used by BNs is very similar to the diagnostic reasoning of clinicians (Feinstein 1973, Elstein and Schwarz 2002), except that it is free of human errors and biases (Elstein 1999). This would facilitate its acceptance by users.

9. Suitable for all Categories. Most of the dimensional approach proposals so far are restricted to specific classes such as personality disorders, developmental disorders, or psychoses (Trull and Widiger 2013, van Os 2009, Krueger et al. 2005, Wildes and Marcus 2013, Hudziak et al. 2007). Conversely, Bayesian diagnosis can be applied to all DSM categories, giving it a distinct advantage over other dimensional approach proposals.

The Usage of Bayesian Networks in Medicine and Psychiatry

BNs are considered the most important approach developed in artificial intelligence for reaching decisions in the face of uncertainty (Charniak 1991). Among the most important applications developed for the purpose of diagnosis are the PATHFINDER project (Heckerman et al. 1992) for lymph node diseases, INTERNIST (Middleton et al. 1991) and Promedas (Wemmenhove et al. 2007) for internal medicine, and HEPAR II (Onisko et al. 2000) for liver diseases. In Turkey, Olmuş and Erbaş (2012) have developed a BN for

the diagnosis of breast cancer. Comprehensive literature on medical and non-medical uses of Bayesian networks can be found in Pourret et al. (2008) and Seixas et al. (2014).

In psychiatry, BNs have been utilized mostly for statistical purposes. Bayesian statistics has recently become popular compared to classical, “frequentist” statistics. Its most important characteristic is that it starts with a prior probability and updates it in view of new evidence. This prior probability may be the result of previous studies as well as a subjective probability estimation (Broemeling 2007). For example, De la Fuente and associates (2011) in an interesting study used BNs to disclose the interdependencies between the symptoms of borderline personality disorder (BPD). The results were interpreted as evidence that BPD symptoms are produced by the same pathophysiological process, suggesting the possibility of using objective neurobiological variables to strengthen the validity of BPD. Krueger et al. (2005), using a Bayesian model, found evidence that comorbidity among externalizing disorders is best modeled by an underlying normally distributed continuum of risk. Arribas et al. (2010) reported that automatic Bayesian classification using fMRI data distinguished schizophrenia, bipolar disorder, and healthy control groups quite successfully. Morales et al. (2013), using the same method, managed to differentiate three Parkinson disease groups with various levels of cognitive impairment. The last two studies are interesting in that they demonstrated that fMRI data can be utilized in psychiatric diagnosis.

In psychiatry, Bayesian statistics has also been used for various aims such as calculating the probability of a child being abused (Best et al. 2013), modeling the dependence between symptoms and neurotransmitter concentrations in depression (Chavrolat et al. 1998), predicting mental retardation in newborns (Mani et al. 1997), and predicting nicotine dependence from genetic data (Ramoni et al. 2009).

On the other hand, few (fewer than ten, to my knowledge) BNs have been developed *as diagnostic tools* in psychiatry. The first was the Bayesian Alcoholism Test (BAT) developed by Korzec et al. (2005) to confirm the diagnosis of “hazardous and harmful alcohol use.” The network’s nodes consisted of biochemical findings such as CDT or ALT, physical examination findings such as BMI or hepatomegaly, and drinking behavior such as early drinking. The authors analyzed the psychometrical properties of BAT and reported that it has better diagnostic properties for confirming hazardous and harmful alcohol use than the GGT and CDT do. The second was developed by Seixas et al. (2014) to diagnose Alzheimer’s disease and mild cognitive impairment. The structure of the network was built based on information supplied by a psychiatrist and automated learning from patient databases. The nodes consisted of predisposing factors, neuropsychological test results, patient demographic data, symptoms, and signs. The third paper is by Sun et al. (2011), who developed a Bayesian

network to diagnose mild cognitive impairment. The primary aim of this study was algorithm development in order to deal with missing data.

In addition to the studies mentioned above, there are five reports presented in various informatics conferences. Estabragh et al. (2011) developed a BN for diagnosing social anxiety disorder, Curiac et al. (2009) for four psychiatric disorders, Pinheiro et al. (2008) and Sun et al. (2007) for Alzheimer’s disease, and Chang et al. (2013) for depression. Finally, Oteniya (2008), for his PhD thesis on computer science, developed two BNs for the diagnosis of dementia. Most of the authors of the nine studies mentioned above are from computer science.

Limitations of Bayesian Diagnosis and its Comparison with the RDoC project

Bayesian diagnosis does not enhance the diagnostic validity of categories. The most important problem of psychiatric diagnosis is the low diagnostic validity of most categories, which stems from the lack of understanding about the nature of mental disorders. Whether categories, as they are defined in DSM, are natural diseases is debatable. As the Bayesian approach proposed in this paper takes present categories as they are, the problems stemming from low diagnostic validity (Kapur et al. 2012) remain unsolved. As stated by Kendler(1999), “[Our problems about psychiatric diagnosis] *may not be solved definitively until we have a detailed understanding of the pathophysiology of the disorders that we treat.*”

Although BNs can make use of some etiological factors and laboratory tests, they do not provide any explanation about the etiological and pathophysiological mechanisms underlying these disorders (Feinstein 1973); they simply calculate the probability of a patient belonging to a given category with the available data. The Bayesian method thus cannot discriminate which nodes are clinical findings and which are etiological factors. It does not increase the sensitivity or specificity of the symptoms and does not uncover unknown etiological factors, new symptoms, or new laboratory tests.

On the other hand, the Research Domain Criteria (RDoC) project is a large and long-term project that aims to elucidate the pathophysiological mechanisms of mental disorders. Its most important difference from the thousands of studies conducted with the same objective is that it does not consider present diagnostic categories. Its long-term aim is to develop a classification and diagnostic method based on the pathophysiological mechanisms of the disorders. When this goal is reached, present categories are expected to be partly or completely superseded by new constructs (Insel et al. 2010).

It is beyond doubt that the diagnostic method that the RDoC project aims to develop is impeccable. However, this is a very long process, and until it is realized, we will continue to treat patients and make clinical decisions as before. This means

that the present system will be in effect indefinitely. Unlike the RDoC, BNs can be readily integrated to present classification systems. Hence, *Bayesian diagnosis may be an intermediate stage between criteria based-diagnosis and the RDoC ideal.*

A Program to Implement Bayesian Diagnosis in Psychiatry

In my opinion, the initial step should be the construction of a BN for each diagnostic class or category in the DSM and ICD. Present diagnostic categories will remain with their names, criteria, and all other properties. Thus, Bayesian and criteria-based diagnoses could be used in combination. Adding BNs and making them optional at first without altering the DSM and ICD will ensure compatibility and facilitate the transition to the new system.

However, constructing a BN is not easy. Designing the topology of the network, determining the dependencies between nodes, and producing conditional probability tables is a continuous and iterative process (van der Gaag 1996, Oteniya 2008) that requires close collaboration between psychiatrists and BN experts.

A single large network that includes all DSM categories may seem attractive, as it could indicate the dependencies between disorders. However, conditional probability tables grow exponentially as the number of arcs between nodes increases, making the task impossible. At the beginning, in order to keep the size manageable, it may be necessary to restrict each network to one or two categories and exclude some less significant variables and relations.

The conditional and unconditional probabilities may be determined by using published epidemiological data and/or psychiatrists' estimations (Charniak 1991, Nikovski 2000). In previously developed BNs, probability estimations of the experts have mostly been used (van der Gaag 1996). This may surprise those who are used to attach importance to objective data, but Bayesian statistics is based on subjective probability estimations—hence their name, “belief networks.” One of their advantages is that they are tolerant of errors and yield satisfactory results with roughly correct probability estimations (Nikovski 2000). However, the best way of producing probability tables is automatic learning from patient data (Onisko 2008). A large volume of data is required for this purpose, but it will accumulate in time. If clinicians from different places enter their patient's data in a standard manner through the web, the amount of collected data will rise rapidly.

Bayesian diagnosis of mental disorders should be realized via a web-based computer program that every clinician has access to. Users should be able to enter their findings and obtain results. High reliability will be ensured by everyone using the same program, similar to using the same diagnostic criteria. As a BN is a piece of software, unlike diagnostic criteria, it

will be updated and developed continuously. In time, new nodes and connections will be added, some will be changed, some deleted. Conditional probability tables will be updated and networks designed separately at the onset will be merged. A user entering the same data a few months apart could get two different results, but our user will know that the second one is more accurate. This mode of development complies with the iterative model mentioned by Kendler and First (2010) and the “living document” philosophy of the DSM-5. I believe that the beta version of the first Bayesian network for diagnosing a mental disorder could be put into trial use in less than one year provided that adequate resources are allocated.

In conclusion, just as criteria-based diagnoses have become the standard due to the authority of the DSM, Bayesian diagnosis should be developed by a central authority and offered to all clinicians. Although this task requires considerable effort and resources, I believe that the potential of the Bayesian approach in being a new paradigm (that does not require a revolutionary change) in psychiatric diagnosis would be well worth the investment.

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