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DECISION ANALYSIS

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In many situations, the price paid for a false-positive diagnosis is more than the price for a false-negative one, and in some situations it is vice versa. Misdiagnosis of severe schizophrenia, requiring admission to a psychiatric ward, can cause severe strain on the patient, on the family, and on the medical care system. A false-positive diagnosis carries more cost than a false-negative diagnosis in this case. On the other hand, a missed diagnosis of leukemia is much more expensive in terms of loss of years of life than a false-positive diagnosis that can possibly be rectified later on.

The chance of error cannot be eliminated altogether but efforts can be made to keep both types of errors to a minimum. This is done by using a sufficiently valid test or by combination of tests where feasible. The fact, however, is that errors do occur. The question is what type of error is more affordable considering the monetary cost, pain, and the risks involved. An approach can be evolved for each patient separately to minimize such costs. The following is the most commonly advocated approach.

Decision Tree

Two important components of evidence-based medicine are probabilities of various outcomes as available in the literature or record, and value judgment regarding action to be taken at different stages. The probabilities are assessed in terms of prevalence, incidence, risk, sensitivity, specificity, predictivity, etc. They must have an effective interface with clinical acumen so that they are examined in the context of actual condition of a patient. Judgment regarding advising a test or not, treating or not treating, treating by medication or by surgery, discharging from the hospital or not discharging, etc., are subjective assessments based on experience and knowledge of the physician. The final outcome depends on judicious mix of these probabilities and the judgments. A decision tree helps to visualize various possibilities, and help act accordingly. Value of a decision tree substantially enhances when 'utility' is assigned to each possible outcome. This utility can be either to the patient such as 0 for death and 1 for full recovery, or to the society. Thus a decision tree maps all the pertinent courses of action and their consequences.

Medical decision trees generally assume the following process of patient management.

Patient→Test→Positive and negative predictivity→Diagnosis→Management strategy based on risks and benefits→Efficiency of the services→Outcome

Out of these, strategy based on risks and benefits is the key for evidence-based decisions. Risks and expected benefits can be assessed as follows. The most favorable situation is that there is no disease and it is correctly excluded. The patient is spared of the unnecessary pain of undergoing the therapy, psychologically feels relieved, and there is no further cost (of treatment). The second satisfying situation is that the presence of disease is correctly diagnosed, properly treated, and recovery is full. The complete spectrum of possibilities is given in Table 1.

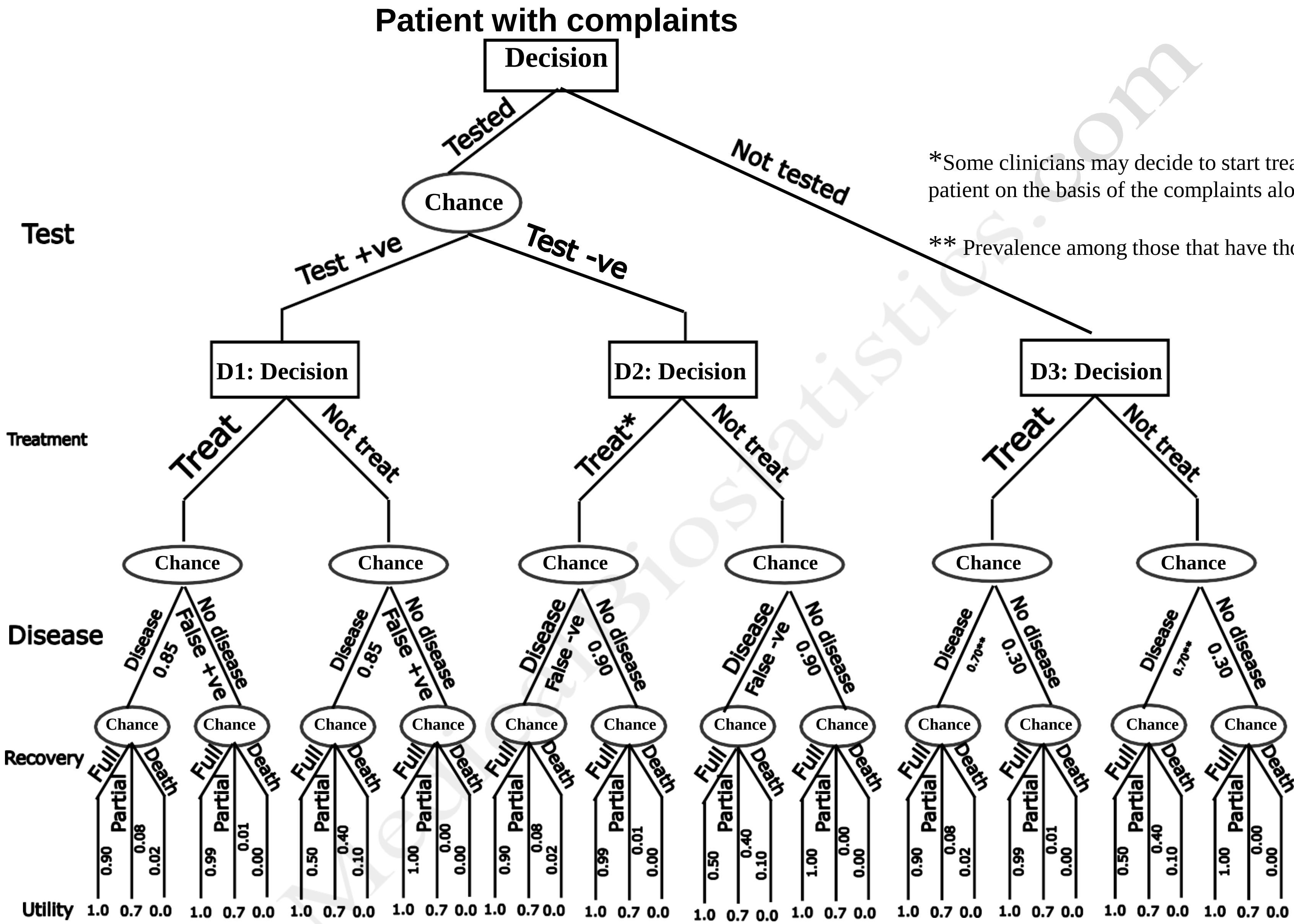
The options provided in Table 1 assume that the decision to treat or not treat is guided solely by the test result—start treatment if the test is positive and no treatment if the test is negative. However, test predictivity is never complete and the test can mislead. Diagnosis may be missed and a misdiagnosis can occur. If a clinician can start treatment despite negative test and not start treatment despite positive test, the possibilities are many more than shown in Table 1. Figure 1 has all such possibilities. The probabilities in this figure are positive predictivity 85 percent and negative predictivity 90 percent. The prevalence of disease among those with the reported complaints is assumed 70 percent. An oval indicates **chance node** where the outcome depends on probability, and a rectangle indicates a judgment node **(more formally, decision node).**

Table 1 Cost involved in various situations of disease, diagnosis and treatment (Treatment only if test is positive)

Situ-ation	Test	Test outcome/ diagnosis	Actual disease	Treat-ment	Recovery	Cost
1.	Done	Positive (Correctly diagnosed)	Present	Yes	Full Partial Nil (death)	Test+Treatment① ①+Disability ①+Loss of life
2.	Done	Positive (Misdiagnosis)	Absent	Yes	Full Partial* Nil*(death)	Test+Treatment① ①+Disability ①+Loss of life
3.	Done	Negative (Diagnosis missed)	Present	No	Full Partial Nil (death)	Test ② ②+Disability ②+Loss of life
4.	Done	Negative (Correctly excluded)	Absent	No	Full	Test ②
5	Not done	Disease present (Correctly diagnosed)	Present	Yes	Full Partial Nil (death)	Treatment ③ ③+Disability ③+Loss of life
6.	Not done	Disease present (Misdiagnosed)	Absent	Yes	Full Partial* Nil*(death)	Treatment ③ ③+Disability ③+Loss of life
7.	Not done	Disease absent (Diagnosis missed)	Present	No	Full Partial	Nil Disability

					Nil (death)	Loss of life
8.	Not done	Disease absent (Correctly excluded)	Absent	No	Full	Nil

*Can occur due to side effect of treatment



*Some clinicians may decide to start treatment of a test negative patient on the basis of the complaints alone

** Prevalence among those that have those complaints

Figure 1 An illustration of a decision tree

A probability is assigned to each grade of recovery in different situations on the basis of available evidence. If evidence is not adequate, subjective probabilities based on experience are used. In Fig. 1, only three grades of recovery are shown for illustration—full, partial and nil—where the last means death. For example, in the case of disease being present and treated, the probability of full recovery is assumed 0.90, of partial recovery 0.08, and of death 0.02 in this example. When disease is present and not treated due to missed diagnosis or otherwise, the probability of full recovery is 0.50, of partial recovery 0.40 and of death 0.10.

In the last row of the figure is the utility assigned to various outcomes. This obviously is 1 for full recovery, and 0 for death. For an intermediary outcome such as recovery with disability, an assessment can be made considering its lifelong implications. In this example, partial recovery is assigned a utility of 0.7. Also one minus the utility can be interpreted as the cost. But a utility 1.0 indicates that the cost of treatment is not factored.

Depending on predictivities, the cost involved, the probabilities of various grades of recovery, and the utility assigned to various outcomes, it is possible to workout the expected benefit of different decisions. For this, the process of folding bottom-up is followed. The following is in terms of multiplication of probabilities and utilities, and their addition. Cost is not adequately factored.

For example, the expected benefit of treatment when test is positive in

a. When the disease is indeed present

$1.0\times0.90 + 0.7\times0.08 + 0.0\times0.02 = 0.956$;

b. When the disease is actually not present (test is false positive)

$1.0\times0.99 + 0.7\times0.01 + 0.0\times0.00 = 0.997$.

Since P(a) = 0.956 and P(b) = 0.997 in this example, the expected benefit of treatment when test is positive

$= 0.956\times0.85 + 0.997\times0.15 = 0.962$.

Similarly, the expected benefit of ‘no treatment’ when test is positive

$= (1.0\times0.50 + 0.7\times0.40 + 0.0\times0.10)\times0.85$

$+ (1.0\times1.0 + 0.7\times0.0 + 0.0\times0.00)\times0.15$

$= 0.78\times0.85 + 1.0\times0.15 = 0.813$.

Clearly, in this example, when test is positive the expected benefit of treatment is much more than of no treatment. This takes care of decision node D1.

Now consider the situation when test is negative.

c. When the disease happens to be present (the test is false negative)

$1.0\times0.90 + 0.7\times0.08 + 0.0\times0.02 = 0.956$;

d. When the disease is indeed not present

$1.0\times0.99 + 0.7\times0.01 + 0.0\times0.00 = 0.997$.

The expected benefit of treatment when test is negative

$= 0.956\times0.10 + 0.997\times0.90 = 0.993.$

Similarly, the expected benefit of 'no treatment' when test is negative

$$= (1.0\times0.50 + 0.7\times0.40 + 0.0\times0.10)\times0.10$$
$$+ (1.0\times1.00 + 0.7\times0.00 + 0.0\times0.00)\times0.90$$
$$= 0.78\times0.10 + 1.0\times0.90 = 0.978.$$

Thus, even when test is negative, expected benefit of treatment is more than of no treatment in these subjects. This is based on the positive and negative predictivities as already specified, and utilities and probabilities of various grades of recovery as in Fig. 1. When these values change, the expected benefit also changes, and your decision to treat or not treat would also change accordingly.

In case no test is done because of exigencies of situation or otherwise, the expected benefit of treatment

$$= (1.0\times0.90 + 0.7\times0.08 + 0.0\times0.02)\times0.70$$
$$+ (1.0\times0.99 + 0.7\times0.01 + 0.0\times0.00)\times0.30$$
$$= 0.956\times0.70 + 0.997\times0.30 = 0.968,$$

and the expected benefit of 'no treatment'

$$= (1.0\times0.50 + 0.7\times0.40 + 0.0\times0.10)\times0.70$$
$$+ (1.0\times1.00 + 0.7\times0.0\times0.00)\times0.30$$
$$= 0.78\times0.70 + 1.0\times0.30 = 0.846.$$

Thus, when prevalence of disease among patients with those complains is 70 percent and all other values as in this example, the expected benefit from treatment is more than no treatment.

All these results are as you would intuitively expect. If utility of partial recovery is only 0.2 and not 0.7, or if the prevalence of disease in this group is only 10 percent, the results would change. You may like to do this as an exercise.

The example illustrates the kind of complexities involved if somebody really wants to take decisions on the basis of tree such as in Fig. 1. The calculations apparently look complex but can be implemented easily with the help of computer based small spreadsheet. By changing values of various utilities and probabilities, the spectrum of expected benefits can be calculated that can help decide what action to take in the best interest of the patient.

This discussion is focused on one particular application of decision trees, namely, in diagnosis and treatment. However, there are several other applications. Su et al. [1] used this approach for an algorithm to diagnose gastric ulcer using mass spectral data. They did not consider treatment options. Blower and Cross [2] discussed decision tree methods in pharmaceutical research and Lunt et al. [3] evaluated a decision tree format for classification of rheumatoid arthritis. These approaches do not consider the utility or the cost as illustrated in the example just discussed, and are similar to the expert system described in the next section.

When resources permit, examine if a tree diagram can help minimize the role of chance in decision and in objective assessment of the outcome for various options that can be exercised in patient management.

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