The division of information into initial conditions and laws, which originated in classical physics in the seventeenth century, plays a key role in all science, as it makes possible study of a phenomenon in situations that vary over a wide range (1).

The term initial conditions refers to parameters which specify a state at the start of an enquiry; for example, initial position and velocity are initial conditions of a falling body whose motion we wish to study.

A law such as Galileo's law of a falling body, on the other hand, is an invariant relationship of velocity being proportional to square of time of fall of a body (2).

The importance of this division is that while the initial conditions vary from falling body to falling body, Galileo's law is applicable to all falling bodies regardless of their initial conditions which facilitates study of motion in any falling body.

We shall argue in this paper that a division of information into initial conditions and laws plays a crucially important role in diagnosis in practice as well.

It is well known from experience that any given disease occurs in different patients with varying presentations and therefore with varying prior probabilities.

For example, acute myocardial infarction (MI) occurs in a 40 year old healthy woman without any cardiac risk factor presenting with highly uncharacteristic chest pain in whom its prior probability is very low at 7 percent (3).

It occurs as well in a 65 year old man with multiple cardiac risk factors presenting with multiple cardiac risk factors in whom its prior probability is very high, say 85 percent.

In practice, we would suspect acute MI from the presentation in both these patients and perform an EKG to evaluate it.

If acute ST elevation EKG changes with likelihood ratio (LR) of 13 for acute MI (4) are observed in both patients, this test result is considered strong evidence due to its diagnostic accuracy of 85 percent (5) from which acute MI is diagnosed (inferred) in both patients.

In this process of diagnosis, the prior probability of acute MI based on its presentation, can be looked upon, we suggest, as an initial condition which varies from patient to patient suspected of having acute MI.

And the relationship between acute ST elevation EKG changes and acute MI which is 85 percent accurate can be looked upon, we suggest, as being lawlike which is applicable to every patient with acute ST elevation EKG changes regardless of prior probability of acute MI (initial condition).

This division into initial condition and law is maintained in the frequentist method which is employed for diagnosis in practice as we have discussed elsewhere (6).

The frequentist method with its division of information into initial condition and law is employed for diagnosis of any disease in practice which has a test capable of generating a result with LR greater than 10 (7).

Thus pulmonary embolism is diagnosed in practice from positive chest CT angiogram, LR 20 (8) and deep vein thrombosis from positive venous ultrasound, LR 16 (9) in any patient regardless of its prior probability (initial condition) in a lawlike manner.

The frequentist method underscores the importance of having a test capable of generating a result with LR greater than 10 in achieving high diagnostic accuracy of a disease. Thus it was only with the availability of perfusion lung scan and chest CT angiogram, which are capable of generating results with LR greater than 10, that diagnosis of pulmonary embolism became highly accurate in patients with varying prior probabilities (initial conditions).

The advantages of the frequentist method, with its division of information into initial condition and law, for diagnosis of a disease in practice are its high diagnostic accuracy of 85 percent or higher and its extreme simplicity.

The importance of making this division becomes apparent on examining the Bayesian method in which this division is not made.

In the Bayesian method, a disease is diagnosed (inferred) in a patient from its posterior probability which is generated by combining its prior probability with the likelihood (LR) of a test result (10).

It is obvious there is no division of information into initial condition and law in the Bayesian method.

The lack of this division creates all sorts of problems which we discuss below if the Bayesian method were to be employed for diagnosis in practice.

As there is no commonly agreed upon level of posterior probability from which a disease is definitively diagnosed (inferred) in a patient in this method, we shall assume this level to be 85 percent or higher.

We note that in the 40 year old woman mentioned above in whom the prior probability of acute MI is 7 percent, we would require a test result with LR of 74 to generate a posterior probability of 85 percent (Appendix 1) from which acute MI would be diagnosed in this patient.

In the 65 year old man mentioned above, in whom the prior probability of acute MI is 85 percent, we would require a test result with LR of only 1 to generate a posterior probability of 85 percent (Appendix 2) from which acute MI would be diagnosed in this patient.

In other patients in whom we suspect acute MI and in whom the prior probability of acute MI varies from 7 percent to 85 percent, we would require test results with likelihood ratios varying from 74 to 1 to generate a posterior probability of 85 percent from which acute MI would be diagnosed in them.

In the Bayesian method, we note, the likelihood ratio of test result needed to diagnose acute MI in a patient depends upon prior probability of acute MI in that patient.

We would require a test result such as a positive cardiac catherization study with LR of 74 to diagnose acute MI in a patient with very low prior probability of 7 percent and a test result such as non-specific T wave EKG changes with LR of 1 to diagnose acuter MI in a patient with very high prior probability of 85 percent.

The employment of so many different tests generating these different test results in different patients for diagnosis of acute MI is impractical, which is why, we believe, the Bayesian method is not employed for diagnosis in practice.

In contrast to the Bayesian method, the frequentist method, with its division of information into initial condition and law, which is employed for diagnosis in practice, achieves a diagnostic accuracy of 85 percent of acute MI in patients with varying prior probabilities with the test result, acute ST elevation EKG changes, which has a likelihood ratio of only 13.

In conclusion, we argue in this paper that division of information into initial condition and law is essential for accurate diagnosis in practice.

Appendix 1

Prior probability of 7 percent = Prior odds of 1/13

Posterior probability of 85 percent = Posterior odds of 85/15

In odds form of Bayes' theorem,

Likelihood ratio = Posterior odds/Prior odds = 85/15 x 13/1 = 74

Appendix 2

Prior probability of 85 percent = Prior odds of 85/15

In odds form of Bayes' theorem,

Likelihood ratio = Posterior odds/Prior odds =85/15 divided by 85/15 = 1

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