Software & Technology as Tools for Clinicians

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Abstract

Analyzing available patent data is becoming an increasingly larger task. Recently more hospitals and clinics are implementing Computer Based Medical Records systems to collect and maintain terabytes of patient data. This may be terabytes of data for each patient.

Since the objective of the clinics and hospitals is to continue to make improvements in quality, safety and cost-effectiveness of care, one question that might be asked is: How much data is "too much data" for a clinician to analyze?

This report suggests that software tools or devices must be used to supplement the clinician's decisions when large amounts of data are involved.

1. Problem Statement

Today more and more data is being analyzed by clinicians. Medical equipment continues to provide more data to assist those clinicians in diagnosing symptoms. In some hospitals, the analysis of data is being outsourced, where the clinicians are part of the SLA (Service Level Agreement) between the hospital and the patient. The outsourced clinicians provide the "expert analysis" when making health related decisions for the patient.

Some hospitals and data analysis companies find it undesirable to use software tools to analyze data and make decisions, or take actions automatically due to possible liability issues. Instead, humans (i.e., the clinicians) are used as the decision-makers in order to avoid possible litigation. The assumption may be that humans are less likely to make erroneous interpretations of the data than automated equipment. Or perhaps they assume that software tools are not currently available to do an adequate job.

Another issue facing hospitals and data analysis companies today is the perception that if software was created to automatically make health-related decisions; it would take years for that software to be approved for use by the FDA.

At the same time, it is recognized that our population is growing older. This increase in the elderly population is a major challenge to the healthcare system in every community. More and more elderly patient data will be collected for analysis, whether monitored in the home and transmitted to clinicians via satellite, or monitored in care centers. Interpreting volumes of patient data will continue to become a bigger and bigger challenge.

Compsim believes that this challenge must be alleviated by using software tools that aid the clinicians in their decision-making activities. Computers never get tired. And when more data needs to be analyzed than can be supported with existing hardware, it is easy to add more processing power. Utilizing software tools can also ultimately reduce the cost of healthcare by reducing undetected errors and by allowing the clinicians to handle more data more effectively.

2. Problem Decomposition / Data Fusion

When physicians and clinicians make diagnostic and treatment decisions, they base their judgment on many factors: patient history, diagnostic test results, environmental factors, direct observations, etc. In some continuous monitoring functions the physician and clinicians have to take into account the drugs that have been dispensed and when they might be absorbed into the blood stream. In these cases they may have to evaluate the original symptoms of the patient and possible reactions to the treatment. The result is a complex, non-linear, multi-variable problem that can change dynamically over time, where the observation of one data point may be insignificant one instant and life-threatening the next.

2.1 Static Data

Referring to data, Miller's (1956) famous "7 +/- 2" rule (an explanation concerning how much information the human brain can handle at any one time) can be restated as: A clinician can handle 7±2 pieces of data at any one time.

An example of this type of analysis is when a pathologist receives a printout from a blood test analyzer. Often there are more than 7 blood tests provided. With each test result, the normal ranges may change with age and differ by gender. If a pathologist is trying to diagnose a particular patient's problem using these test results, they must look for deviations or patterns. So, not only are there more than 7 types of data, there are multiple "scenarios" that must be considered in order to determine a specific diagnose. We suggest that the way that a human interprets this information is to prioritize the information and make judgmental decisions based on what appears to be the most important data. This may sometimes yield results that do not incorporate ALL of the data available.

We suggest that a solution that evaluates ALL available information and provides an explanation of the analysis would be helpful to clinicians, especially if it could explain why other diagnoses might be inappropriate.

2.2 Dynamic Data

Using the same 7 +/- 2 Rule described above it is very easy to see that if data is being analyzed that is *constantly changing*, an analyst could potentially have a much more difficult time determining what is normal and what is problematic. They must use some type of indicators from some software-based system.

An example of this type of analysis is when a person is supervising a patient that has several devices monitoring their bodily functions. Patient monitoring systems are good examples of applications that require people to make decisions in a continually changing environment. The monitoring devices will likely have some alarm conditions built into them, depending on the device. In most cases today, these are static or fixed alarm conditions, where individual measurements are compared against fixed values. In many situations, however, the patient needs to be monitored during treatment when the measured values are "expected" to change. Today this means that a clinician needs to observe the readings manually and interpret whether the changing readings are progressing at an acceptable rate or whether other treatment options need to be explored. Because of the expense of assigning human observers to continually monitor all values, this is commonly done on a periodic basis. Because the human clinician is probably monitoring several patients, there is likely a time delay each time the clinician has to refresh their memories on each case history. We believe that by utilizing software applications that can analyze data on a continuous basis and make decisions (or take actions), patient safety could very well be improved in this type of environment.

2.3 Humans are Non-Linear Systems

In the medical domain, humans can be considered non-linear systems. Medical statistics define normal values by collecting data across many subjects in test studies. Standard deviation curves define the distribution of test results. When the normal distribution is different as a person ages, the statistics are often categorized into different buckets, suggesting that as a person ages they periodically jump from one bucket to another. Some medical diagnostic equipment will present individual test results graphically (showing how they fit within the normal range) and others present the results numerically. In many cases, an individual test may be impacted by external factors (diet for example, or other medications). To make a diagnosis, the clinician has to combine the "relatively valued" data items and evaluate how the combined data sets match alternative diagnoses. The clinician's "experience" is the dominant process for accumulating or combining the data. There is often only a very loose coupling between the diagnosis and the process the clinician used to make the diagnosis. The notes taken by the clinician to document the analysis can, almost never, tell the complete story. This is partly due to the inability of the human written language to accurately describe non-linear systems. It is also due to the complexity of the reasoning that is applied.

2.4 Data Fusion

The proposed solution allows judgmental rules to be defined as a set of inter-related curves that can be fused or combined to recognize the importance of different data items and show how the data items are related. A graphical source code language is used to document the method of interpreting the data. Rather than a series of "IF, THEN, ELSE" rules, all of the data is combined and interpreted together. The reasoning model is created by identifying the data items for their importance and wiring data items together to define how they are related. Curves can also be generated to define how the data is expected to change over time.

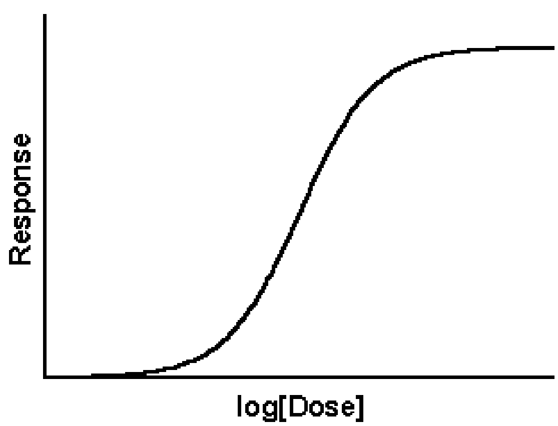
When implemented as a cognitive solution, the graphical rules are translated into conventional source code. This includes a small amount of processing code and associated tables that define the importance of information items and the relationships between them. This code can then be integrated into software applications and devices to aid the clinicians in their data analysis activities.

3. Tools to Describe Non-Linear Dynamic Systems

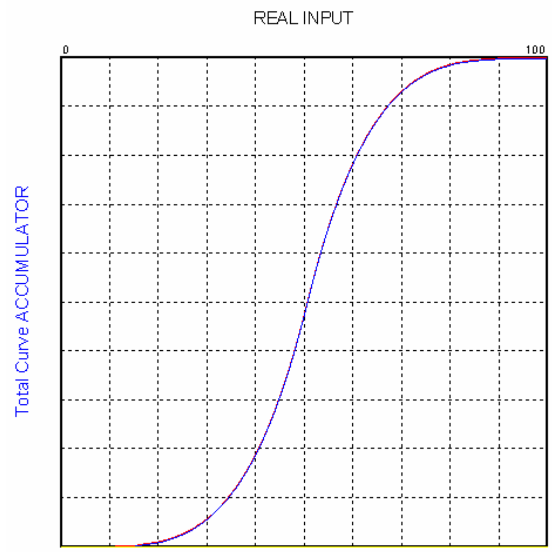
KEEL Technology and KEEL engines operate like an analog computer. When designing an application using a KEEL system, the designer thinks in terms of "curves" (non-linear relationships).

3.1 Dose-Response Curves

The following example was taken from an article entitled "Introducing dose-response curves" by GraphPad Software, Inc., 1999: "Dose-response curves can be used to plot the results of many kinds of experiments. The X-axis plots concentration of a drug or hormone. The Y-axis plots response, which could be almost anything. For example, the response might be enzyme activity, accumulation of an intracellular second messenger, membrane potential, secretion of a hormone, heart rate or contraction of a muscle."

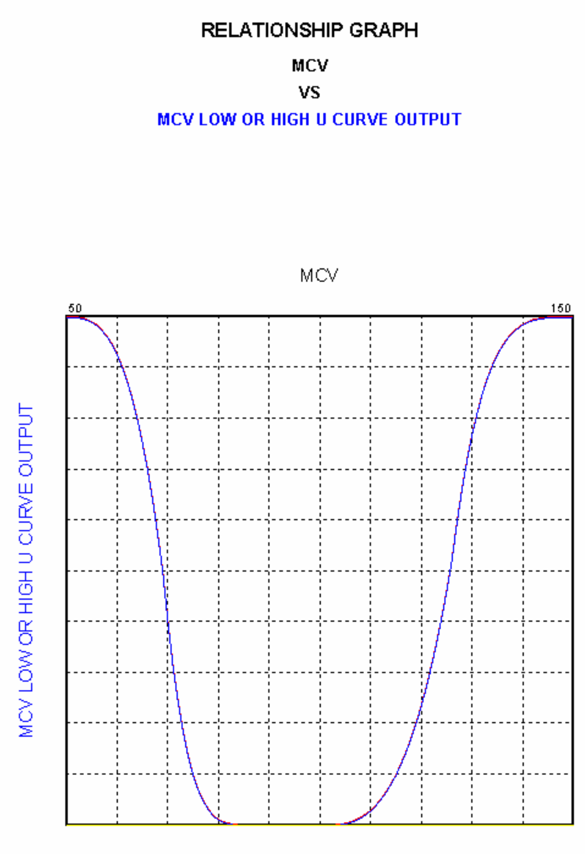


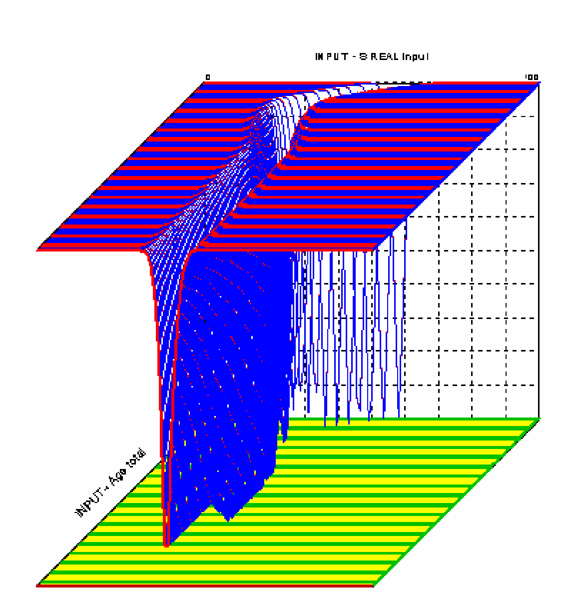
The next picture shows a similar curve created using the KEEL Toolkit. Note that any of the curves can be tuned to very finite numbers since they need to match statistics gathered by the medical industry.



3.2 Normal Distribution in Blood Tests

Another example in the medical arena is curves that are used to define normal ranges for blood tests. The following diagram shows the curve representing MCV (mean cell volume) for an "adult". This curve is "static", meaning that it doesn't change as the person ages. This, however, is not true for all situations.





3.3 Age Affects Curves Used in Blood Tests

As stated earlier, a person's age is thought of in terms of steps. After babies are born, they may be categorized as children until they turn twelve years old. They may then be classified as young adults until the magic age of eighteen, when suddenly they may be classified as adults. Other categorization schemes for other diagnostic test results may define other bucket sets. While it is convenient, statistically, to categorize data as static step values, this is inconsistent with the real-world.

A more complex example is the diagnosis of anemia in children. When adult anemia is analyzed there is one range for each of the blood samples that are analyzed (see section 3.2 above). However, there are at least twenty-two (22) different age groups used for children (prenatal, cord, infant, etc.). Each of the ages has different normal value curves for each test. The following snapshot shows a more realistic 3D representation of the curve depicting how the normal distribution moves through the first year of life.

3.4 Complex Problem

The complexity of the problem is magnified when one has to consider that each diagnostic test has its own dynamics. Using the example of diagnosing child anemia, the impact of age is different for each blood test. Even with the old method of categorizing blood tests into age categories, this requires the clinician to evaluate complex relationships. The clinician either has to memorize all of the normal values for all of the blood tests, for all of the age categories, or they have to do an extensive manual comparison for each diagnosis. If there are other items that need to be considered (diet, medication, etc.) then the magnitude of the problem extends exponentially.

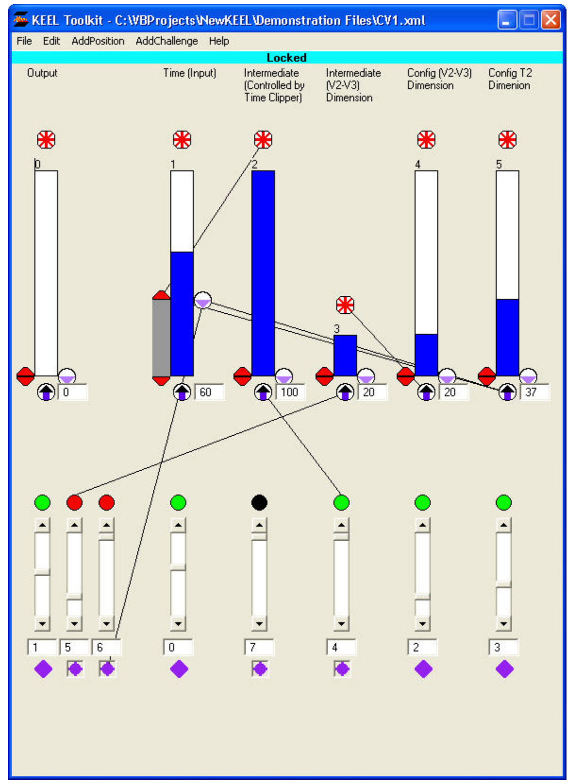
3.5 Continuous Diagnosis of Complex Systems

So far, we have been discussing static data analysis. This addresses the situations where the clinician studies a set of test results and makes a diagnosis. An even more complex situation can be defined as one where the data analysis must be performed continually. An example of this might be a heart rate monitor. It is one thing to monitor the heart rate for a "change" or for a specific "event", but it is another to monitor the heart rate as part of an overall treatment scheme where the observation must be considered along with expected changes or along with other patient reactions. For example, a patient may be given a drug to treat some malady. It will take some time for the drug to be absorbed into the blood stream. Once it is absorbed, several observations may be "expected". Based on one or more of these observations, several other changes might occur (some good, some bad). Some of these may require immediate attention by the physician, while others may be reviewed during normal rounds. Still others may suggest that other activities be initiated. Each of these diagnostic components may have different time constants. Today, much of this activity is performed by humans in an intensive care environment. The clinicians are trained to monitor changes and make judgmental decisions about calling for immediate attention. It may be more effective to allow the physician to define expectations as a set of triggered curves

4.0 A Graphical Language to Define Non-Linear Dynamic Systems

Compsim's KEEL Technology is suggested as a potential solution to these complex non-linear problems. The following screen shot shows the graphical source code language that is used to define the data items and their importance in the decision-making process. The "wires" are used to define the relationships. Using the graphical language, the curves can be developed without the use of conventional IF | THEN | ELSE code or complex formulas. Data items like "age" can be used to shift curves across the age spectrum. Other curves can be used to trigger events or other monitoring functions, should certain events or values be detected.

The result is a set of tools to define and test complex non-linear systems. And because the decisions and actions are based on the graphical language, they are completely explainable and auditable. By viewing a snapshot of the inputs, one can "see" how "all" data is integrated into the diagnosis. External software tools can be created to provide a detailed textual explanation of any diagnosis or treatment activity.



5. Conclusion

Using software applications as tools can improve patient safety and save on bottom line costs by reducing errors made by humans, because more data can be handled automatically by software than by humans.

KEEL (Knowledge Enhanced Electronic Logic) technology is suggested as a technology that can be used to create the cognitive components of software applications that help clinicians analyze data. Whether the data is static or continuously changing or whether there are contributing events that need to be incorporated into the analysis, there is often too much data for the human brain to handle. KEEL Technology can assist in the creation of solutions that can be explained and audited by humans.

REFERENCES

- Miller, G. A. (1956). The magical number seven plus or minus two: Some limits on our capacity for processing information. Psychological Review, 63, 81-97

- Article entitled "Introducing dose-response curves" by GraphPad Software, Inc., 1999

Compsim LLC (http://www.compsim.com) is a provider of next generation cognitive technology for application in automotive, industrial automation, medical, military, governmental, enterprise software and electronic gaming markets. The company is headquartered in Brookfield, Wisconsin.
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