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Advances in the application of research in diagnostics, intensive care and medical treatments

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Abstract

We encourage the growth of operations research/ management science theory and methods in the field included in health and medical care for the purpose of continuously improving processes included in this field. By focusing on the growth on data analytics, statistics, applied mathematics, computer methods including machine learning of artificial intelligence, the future of health cared methods will change in a positive manner. The development of computerized methods to and the growth of data systems produced ample materials for artificial intelligence to develop and to bring physician assistance programs to enable better, quicker and more analytical programs to better health and medical care. This includes applications in intensive care as well as diagnostic therapies. We focus on examples in the use of the promising developments in the quality and continuous improvement in process control where there are great possibilities of change in both medical applications as well as improve the management of hospital and other medical facilities.

Keywords: Quality; Diagnostic testing; Data analytics; Artificial intelligence; Autoregressive moving average; Multivariate; Autocorrelation

Introduction

Management Science/Operations Research is now everywhere one looks from the production of most automotive parts to the check-out lines at most supermarkets and similar places. We refer to this as automation but it is the advances in computer technologies that drove this mechanization of seemingly simple but technological advanced tasks to streamline production methodologies. The growth of these technologies in the future will accelerated by breakthroughs in artificial intelligence which will continue the mechanization of tasks improve the quality of output, Artificial intelligence (AI) includes the Leadership in Forensic Science Laboratories; Forensic Laboratory Key Business Metrics and Cost–Benefit Analyses; Laboratory Excellence and Ethics: An Essential Association; Laboratory Excellence and Ethics: An Essential Association; ISO Accreditation Implementation: A Framework to Implement a Quality and Writing Policies and Procedures. To incorporate AI into heath care procedures is not simple but it includes the methodology of statistical/ mathematical science as it applies the data driven methodologies. In this study, we focus on one such plan that involves the analytics associated with a volume of diagnostic tests to generate plans to generate treatments.

Automating the Quality Movement in Diagnostics

Improvements in diagnostic care whether in hospitals, treatment and diagnostic centers and other health care units are a central function of quality health care. In many places, they are the principal methods by which patients can secure care. The example of Planned Parenthood Clinics is one such example where the patients can receive care and treatment in an affordable and often convenient place. They provide services that often are not available to those who do not have sufficient (perhaps, or any) places to achieve affordable care. A client enters the clinic to possibly have diagnosed a severe set of conditions in which scientific tests are given to determine a diagnosis and therapeutic plan to produce a treatment to successfully reduce the problem and achieve positive results. The process includes a ***total quality movement (TQM)*** which is a plan to achieve a successful outcome to the patient's health problem. In the future we, expect AI and TQM movement to spread everywhere. Look at the current research in automobiles and the relative changes made by the driverless vehicle.

To consider the depth of Operations Research/Management Science topics in health care include the following manuscripts by Jarrett [2008 with X. Pan and 1981, 2015, 2016], In addition, others including Patel et al., 2009, Machado and Costa, 2010, Khoo and Quah, 2003 and more recently, Acampora et al., 2013 added specific illustrations of new computer based methods. Technology firms such as Google, Amazon, Microsoft, and Apple in recent year made huge investments in artificial intelligence to deliver tailored search results and build items called personal virtual assistants. The methodology is seeping down to hospital care and other forms of diagnostic and treatment methodology in health care in general. With reforms in health care and health care reform law will enable both physicians and other health care personnel to be assisted in choosing medicines and treatments for patients in both an efficient and timely manner. For example, a physician has patient with a particular diagnoses will be able to choose the best medicine to counter the effect of a severe diagnoses quickly. With the huge number of medicines available at a physicians' ability to prescribe, much of decision will be automated thanks in part to the push for computer systems to prescribe the best treatment available from medical science. No longer will a physician need to observe volumes of data bases to find the optimal treatment. The computer will find and inform health care personnel to act quickly and optimally.

Today, data collection by health statistician include volumes of patient demographic, clinical and billing data which in an electronic format for analysis by intelligent software For these difficult tasks AI software can analyze quickly to perform the tasks of recommending medicines, treatment protocols and general advice to assist physicians in attacking the problems associated with difficult diagnoses. For example, applications of AI have been utilized in intensive care for nearly a generation; Hanson and Marshall, 2001, and more recently Liu and Salinas, 2017. In other examples, new digital devices and home tests are allowing a more thorough patient examination remotely, which addresses some of the previous setbacks of telemedicine. Remote diagnostic tools such as *Tyto, Scanadu and Med Wand* are expanding the perception of telemedicine. Heartbeat and respiration rate can now be checked remotely. The same is true for blood pressure, blood glucose, body temperature, and oxygen levels. A device may contain a high-definition camera which will examine to look down throats and ear canals. Cameras can also provide high-resolution images of skin to examine lesions, suspicious skin changes and other dermatology examinations. Urine-testing kits may also be employed in the home or specific diagnostic centers to provide information to medical personnel to suggest a treatment without the patient being with the medical personnel.

At this point, we should consider automated statistical quality control or (ASQC) or automated statistical process control (ASPC) as it applies in TQM. These terms are no longer new in diagnostic and treatment terminology, however, they are based on previous applications in industry, and banking and everywhere one seeks assistance in the analysis of data where the timing of decisions is very important. TQM is the field that ensures that management maintains standards set and continually improves the processing successful goals and achievements. Instead of final, end-of-serve inspection (whether the patient if found healthy or not after the treatment ends. TQM according to Lee and Wang, 2003, and Weihs and Jessenberger, 1999, provides. Otherwise, instead of end-of-service inspection and decision making TQM emphasizes prevention, integrated source inspection, process control and continuous improvement [See Woodall, 2005, Papaioannon et al. 2010A and 2010B]. The mitigating of risks of Type I and Type II errors are the prime purpose of these methods. In addition, known, with AI the process will provide software, services, and analytics solutions to the ambulatory care market. We are a healthcare information technology and services company that delivers the foundational capabilities to organizations that want to promote healthy communities The technology provides a customizable platform that empowers physician success, enriches the patient care experience and lowers the cost of healthcare and in turn health insurance. Stated simply, AISQC monitors the incidence characterized by the results of multiple tests on a similar fluid per period of a short interval over a lengthy period (10 to 20 weeks, for example). The monitoring requires an intelligent system analyzing items (control charts, for example) and seeking whether there are common causes of variation or special causes of variation. In industrial applications, these were entitled ***Shewhart*** charts. Later others suggested additional methods including the use of exponentially weighted moving average (EWMA) control charts, Griggs and Spiegelhalter, 2007.

The great rise of health information systems enables AI in the very early stages of its development to match one's own intelligence. Computers certainly cannot physicians, however, AI software and computer technology are capable of processing vast amounts of data and identifying patterns that humans cannot.AI solves the complex algorithms that analyze this data and is a useful tool to take full advantage of electronic medical records, transforming them from mere e-filing cabinets into full-fledged physician analysts' who can deliver clinically relevant, high quality data in real time.

AISPC and AISQC in Health Care Environments

SPC (SQC) environments usually assume a steady process behavior where the influence of dynamic behavior where the influence of dynamic behavior does not exist or is ignored. The focus of control where there is only one variable (i.e., medical test) over a lengthy interval of time. SPC controls for the changes in either the measure of location or dispersion or both. These procedures as practiced in each phase may disturb the flow of the service production process and operations. We not that in recent years the use of SPC to address processes characterized by more than one test or treatment emerged. First, we review the basic Univariate procedures to improve the process of SPC and allow AI to enter the process.

Shewhart control charts were the central foundation of univariate (one variable) SPC has a major flaw. The process considers only one piece of data, the last data point, and does not carry the memory of the previous data collected. Often, a small change in the mean of a random variable is not likely to be detected quickly. Griggs and Spiegelhalter, 2007, EWMA control charts improved upon the detection process of small process shifts. Rapid detection of relatively small changes in the characteristic of interest and ease of computations through recursive equations are some of the important properties of the EWMA control chart that makes the process attractive and ease to use intelligent software to detect changes.

The EWMA chart is used extensively in time series modeling where the data contains a gradual drift (Box and Draper, 1998) EWMA provides for identifying gradual shifts in medical tests by predicting where the observation will be in the next period of time. Hence, the EWMA process improves decision support in the future and is dynamic (Hunter, 1986) The EWMA statistic for monitoring the results of lengthy period of tests having short interval when the actual tests are performed. Furthermore, the method gives less and less weight to data as they become more remote in time. Montgomery, 2013 contains the development of models for finding control limits in this univariate process, but appear4s to be another example of where intelligent software applies.

Additional Applications Using Univariate Models

In many applications of univariate analysis, the sample size used in the test process is one. Stated differently, the sample consists of an individual unit [Montgomery and Runger, 2003]. The control chart for sample of 1 (the Individual Chart) employs a moving average of two successive observations to estimate the process variability. Obviously, small samples lead to incorrect decisions (stated as an increase in the probability of a Type II error. Sonesson and Bock, 2003, pointed out problems and issues associated with statistically based evaluations which must be included in intelligent software. A solution may be provided by examining ***average run length*** (ARL) of a proposed solution over a variety of alternative process shifts. ARL performance for an in-control state and for a single shift in a process for which the proposed detection program optimizes must be evaluated. If the system is not optimized, misplaced control limits may result. The system for detection of shifts is sub-optimized and better techniques should be sought. Yeh and Hwang, 2004 suggest processes whereby the units are dynamic. In provider of care treatments, the distinction between Phases I and II of SQC solutions is often not clear. Hence, ARL is often the choice used to assist the providers of care with the assistance they need to recommend courses of treatment.

Alwan (1992) found that the great majority of SPC applications studied results in control charts with misplaced control limits and essentially false signals to the providers of care. The misplacement results from auto correlated process observation. The auto correlated time series observations violate an assumption associated with Shewhart control charts (Woodall, 2005). Autocorrelation of process observations is common in many applications, i.e., cast steel [Alwan, 2000], wastewater treatment plants [Berthouex et al., 1978], chemical processes, [Montgomery and Mastrangelo, 1991] and many other processes in the health care industry, especially diagnostic care and similar applications. In addition, Alwan and Roberts, 1988, suggested using an autoregressive integrated moving average (ARIMA) charts for decision analysis. Continuous intelligent software can be of particular aide to identification of the appropriate methods for decision analysis if one follows the works of Atienza et al., Box et al., 2008, West et al., 2002 who employed ARIMA modeling with Intervention; and, in addition, Jarrett, 2016A and 2016B, summarized many of these method in SPC. All these models are in the process of being computerized to develop intelligent systems that will enable computers intelligently point to optimal patient treatments and diagnoses. The notion of physicians have patient centered diagnostic programs using AI will be of immense aid.

Multivariate Quality Controls (MQC) and AI

Multivariate methods uses additional analyses due to having two or more variables which are the results several or more diagnostic procedures to determine specific plan of care (treatment). The use of univariate analysis may lead to incorrect interpretation of data due to the co-integration of the tests performed. The most popular multivariate (MQC) methods are those based on the Hotelling $T^{(2)}$ distribution, Woodall, 2005, West et al., 2002 and Yang and Rahim, 2005 multivariate exponential moving average method [MEWMA, Elsayed and Zhang, 2007] Other approaches, such as control ellipse for two correlated variables. There are other MQC methods. Other MQC methods include those developed by Kalagonda and Kulkarni, 2003 and 2004; Jarrett and Pan, 2006, 2007A, 2007B and 2013; Vanhatalo and Kulachi, 2014; and Billen et al., 2016. All the above MQC modelers produced results that achieve superiority to SQC analysis because of one or more of the following factors:

1. The control region of variables is represented by an ellipse rather than parallel lines
2. The Intelligent software is programed to maintain a specific probability of a Type I error in the analysis.
3. The determination of whether the process is out of control is a single control limit (ARL)
4. Correcting T^2 based MQC analysis there autocorrelation is present.
5. Use of MEWMA, when time series methods have unique schemes.

As a result the above methods indicate that intelligent software cannot ignore the various possibilities to lead to non-optimal decisions. However, proper AI methods will adjust to new research and patient assisted analytical software will be of great use to find diagnoses that enable one to use AI to solve difficulties with patient care.

Summary and Conclusion

The purpose of this study is encourage the growth in a very important and growing industry called artificial intelligence. AI based platforms for digital transformation will play a growing role in patient diagnoses health programs. The growth will occur in treatment and emergency care centers as well as intensive care units. Intelligent software is being developed which will suggest to physicians and other health care workers the meaning of studying data bases of information data analytics. In turn, intelligent software will prescribe and set protocols for treatments of difficult prognoses and intensive care. Intelligent programs are AI-based platform for digital transformation. They are modular and an interconnected mixture of flexible digital technologies that span from robotic automation to machine learning. The programs learn over time and produce new ways to arrive at results. The study indicates that new ways to get results and in timely fashion. The blending of intelligent software and comprehensive data analytics will eventually move health care analysts from the task of interpreting results to have protocols produced for them. Intelligent software will blend seamlessly with a decision maker's operations insights and produce a unique domain expertise to create better analytical conclusions in the real world. By examining quality operations, we observe how AI shares the burdens of care and assists health care personnel in achieving their goals. As stated earlier, AI in health care incorporates AI into many heath care procedures that are not simple but includes the methodology of statistical/ mathematical science as it applies the data driven methodologies.

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