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Digital Optimization Decision Analysis of Reliability Life Research

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Abstract: With the advent of the global information era and the rapid development of modern science, technology, and economy, intelligent optimization algorithms and statistical optimization analysis have become current and future frontier hot topics in life sciences, artificial intelligence, neural computing, and scientific decision-making. This paper uses a variety of efficient and reliable scientific computing methods such as modern statistical optimization analysis, intelligent optimization algorithms, and big data analysis to discuss life sciences, artificial intelligence, neural computing, ecological environment and other fields in a comprehensive and multi-perspective manner. The method is advanced, and the effect reliable.

Keywords Survival life analysis; Intelligent optimization algorithm; neural computing; Big data statistical information; Optimal decision and control; Sustainable development strategy

INTRODUCTION

The world is the information world as well as the material world. In recent years, intelligent optimization algorithms in the fields of big data statistical survival life analysis and neural computing have become the most challenging frontier hot topics in the current and future research of biostatisticians, mathematicians and computer scientists. With the advent of the global information age and the explosion of information brought by the rapid development of social informatization, networking, technology, and economy, the issues involved in statistical analysis and information decision-making have become more and more complex, and the research on information decision-making methods has become a multi-level, multi-disciplinary, and all-round system. Decision-making not only requires analysis, screening, and judgment of a large amount of relevant information, and then creative plan formulation, evaluation, selection and implementation, but also requires fast, accurate and comprehensive information support [Long, et. al., 2018]. On the basis of, in-depth exploration and discussion of the random statistical inference and intelligent optimization algorithm problem of a kind of random effect model in neural computing for the survival and life analysis of human and biological populations, the optimal control and decision results of random signals in this generalized process can be obtained. It provides a very effective big data statistical optimization analysis and mathematical processing methods and intelligent optimization algorithms for further studying this kind of process, such as research on brain aging and related problems in neural computing. The method is advanced, and the effect is reliable.

ESTABLISHMENT OF SEVERAL KINDS OF IDEAL RANDOMLY CENSORED DISTRIBUTIONS IN THE ANALYSIS OF SURVIVAL LIFE

(1) Suppose

$$f(x)=\begin{cases} 0 \\ s\dfrac{1}{\sqrt{2\pi\zeta}}\exp\left(-\dfrac{1}{2}\left[\dfrac{x-\lambda}{\zeta}\right]^2\right) \end{cases}$$

$$s=\frac{1}{\varphi[(\mu-\lambda)/\zeta]}=\frac{1}{P(Y\le\mu)}$$

Where Y has Distribution $N(\lambda,\zeta^2)$.

(2) Suppose

$$f(x)=\begin{cases} 0 \\ s\dfrac{1}{\sqrt{2\pi\zeta}}\exp\left(-\dfrac{1}{2}\left[\dfrac{x-\lambda}{\zeta}\right]^2\right) \end{cases}$$

$$s=\left[1-\varphi\left(\frac{l-\lambda}{\zeta}\right)\right]^{-1}$$

The above truncated concept of the normal life distribution can be applied to other life distributions. There is an example that one exponential life distribution random variable X which can be truncated on the left of $X=l$ with the following probability density function

$$f(x)=\begin{cases} 0 & When \quad x<l \\ a\beta e^{-\beta x} & When \quad x\ge l \end{cases}$$

$$P(X=j)=\begin{cases} 0 \\ a\dfrac{\mu^j}{j!}e^{-\mu} \end{cases}$$

Where a can be decided according to the condition $\sum_{j=0}^{\infty} P(X=j)=1$, we can have

$$a=\frac{1}{\sum_{j=0}^{s}\left(\mu^j/r!\right)e^{-\mu}}$$

so

$$P(X=j)=\frac{\mu^j}{j!}\frac{1}{\sum_{r=0}^{s}\left(\mu^j/r!\right)} \quad , j=0,1,\cdots,s$$

and the others are equal to 0.

A Statistical Inference Optimization Algorithm to Improve Statistical Information Retrieval in the Research of Reliability Survival Life

We observe M variables Y_{ij} scattered in S groups: $Y_{ij}(i=1,\cdots,n_i;\ j=1,\cdots,s)$.

Suppose

$$Y_{ij}\sim f_{ij}(\beta_i;\zeta_j) \tag{1}$$

$$\mathrm{var}(Y_{ij})=E[\mathrm{var}(Y_{ij}\mid\beta_i)]+\mathrm{var}[E(Y_{ij}\mid\beta_i)] \tag{2}$$

We can define

$$\eta_{ij}=\frac{\mathrm{var}[E(Y_{ij}\mid\beta_i)]}{\mathrm{var}(Y_{ij})} \tag{3}$$

(Ⅰ) $\xi_{ijj'}=\xi_i$ for all i,i'

(Ⅱ) $\mu_{ij}=\mu_i$ for all i

(Ⅲ)The random effect model belongs to a class specified by

$$E(Y_{ij}\mid\beta_i)=S_{ij}[\mu_i(\beta_i)+w_{ij}]\ and\ \mathrm{var}(Y_{ij}\mid\beta_i)=S_{ij}{}^2[\zeta_i{}^2(\beta_i)+\varphi_{ij}(\beta_i)] \tag{4}$$

Where S_{ij} and w_{ij} are deterministic quantities, and $E[\varphi_{ij}(\beta_i)]=0$ and $\varphi_{ij}(\beta_i)>\zeta_i{}^2(\beta_i)$. In addition , these propositions imply:

$When\ j=s+1$ (Ⅳ) $\xi_i=\xi$

$When\ j=0,1,\cdots,s$ (Ⅴ) $\mu_i=\mu$ and $\zeta_i{}^2(\beta_i)=\zeta^2(\beta_i)$; then $\mu_i=\xi_i=\xi$.

$$\mathrm{cov}(Y_{ij},Y_{ij'})=\mathrm{cov}[E(Y_{ij}\mid\beta_i),E(Y_{ij}{}'\mid\beta_i)] \tag{5}$$

This is equal to

$$E\{S_{ij}[\mu_i(\beta_i)+w_{ij}]-S_{ij}[E(\mu_i(\beta_i))+w_{ij}]\}\{S_{ij'}[\mu_i(\beta_i)+w_{ij'}]-S_{ij'}[E(\mu_i(\beta_i))+w_{ij'}]\}=S_{ij}S_{ij'}\mathrm{var}[\mu_i(\beta_i)]$$

Using (2),we have

$$\mathrm{var}(Y_{ij})=\{E[\beta_i{}^2(\zeta_i)]+\mathrm{var}[\mu_i(\beta_i)]\}S_{ij}{}^2$$

and thus

$$\xi_{ijj'}=\frac{\mathrm{var}[\mu_i(\beta_i)]}{E[\zeta_i{}^2(\beta_i)]+\mathrm{var}[\mu_i(\beta_i)]}=\xi_i$$

Using(3) and $E(Y_{ij}\mid\beta_i)=S_{ij}[\mu_i(\beta)+w_{ij}]$, we obtain

$$\eta_{ij}=\frac{\mathrm{var}[\mu_i(\beta_i)]}{E[\zeta_i{}^2(\beta_i)]+\mathrm{var}[\mu_i(\beta_i)]}=\eta_i=\xi_i\,.$$

Then we demonstrate that (Ⅰ) implies (Ⅲ): Let $E(Y_{ij}\mid\beta_i)=g_{ij}(\beta_i)$ and $\mathrm{var}(Y_{ij}\mid\beta_i)=Q_{ij}(\beta_i)$. From (Ⅰ) we have

$$\xi_{ijj'}=\frac{\mathrm{cov}(Y_{ij},Y_{ij'})}{[\mathrm{var}(Y_{ij})\mathrm{var}[Y_{ij'}]^{1/2}}=\xi_i\,.$$

$$\frac{\mathrm{cov}(Y_{ij},Y_{ij'})}{S_{ij}S_{ij'}}=E\left\{\frac{g_{ij}(\beta_i)}{S_{ij}}-\frac{E[g_{ij}(\beta_i)]}{S_{ij}}\right\}\left\{\frac{g_{ij'}(\beta_i)}{S_{ij'}}-\frac{E[g_{ij'}(\beta_i)]}{S_{ij'}}\right\}=P_i\,,$$

for all j,j'. This implies that

$$\frac{g_{ij}(\beta_i)}{S_{ij}}=\frac{E[g_{ij}(\beta_i)]}{S_{ij}}=\mu_j(\beta_i) \quad \text{with}$$

$\mathrm{var}[\mu_i(\beta_i)]=P_i$,

and thus $E(Y_{ij}\mid\beta_i)=g_{ij}(\beta_i)=S_{ij}[\mu_i(\beta_i)+\zeta_{ij}]$ with $\zeta_{ij}=E[g_{ij}(\beta_i)]\big/S_{ij}$ .We have also $\mathrm{var}(Y_{ij})=S_{ij}{}^2H_i$ and thus, using (2),

$$E[\mathrm{Q}_{ij}(\beta_i)]+\mathrm{var}[g_{ij}(\beta_i)]=S_{ij}{}^2H_i\,.$$

Since $\mathrm{var}(g_{ij}(\beta_{ij}))=S_{ij}{}^2\,\mathrm{var}[\mu_i(\beta_i)]=S_{ij}{}^2P_i$,we have

$$E[Q_{ij}(\beta_i)] = S_{ij}^2[H_i - P_i] = S_{ij}^2 E[\zeta_i^2(\beta_i)],$$

and

$$\text{var}(Y_{ij} \mid \beta_i) = Q_{ij}(\beta_i) = S_{ij}^2\zeta_i^2(\beta_i) + \varphi_{ij}(\beta_i),$$

With $E[\zeta_i^2(\beta_i)] = H_i - P_i$ and $E[\varphi_{ij}(\beta_i)] = 0$. With the same principles we can demonstrate that (II) implies (III).

$$\text{var}(Y) = \frac{\text{var}(Y_{ij})}{M}\left[1 + \left(\frac{\sum n_i^2}{M} - 1\right)\xi\right] \tag{6}$$

In the linear model, $\beta_i = c_i$ and we have $E[\text{var}(Y_{ij} \mid \beta_i)] = \zeta_e^2$ and $\text{var}[E(Y_{ij} \mid \beta_i)] = \zeta_c^2$, hence

$$\xi = \frac{\zeta_c^2}{\zeta_e^2 + \zeta_c^2} = \xi_a$$

If Y_{ij} is c Bernoulli variable with parameter $\beta_i = \xi_i$,we have $[E(Y_{ij} \mid \beta_i)] = \beta_i$, $\text{var}[E(Y_{ij} \mid \beta_i)] = \text{var}(\beta_i)$, $E(Y_{ij}) = E(\beta_i) = \pi$ and $\text{var}(Y_{ij}) = \pi(1-\pi)$; hence

$$\xi = \frac{\text{var}(\beta_i)}{\pi(1-\pi)} = \xi_b$$

$$Y_{ij} = \lambda + \beta_i + aX_{ij} + \varepsilon_{ij}$$

$$P_{ij} = \frac{(\mu_i + w_{ij})(E(\mu_i) + w_{ij})}{2w_{ij}E(\mu_i) + w_{ij}^2 + B}$$

Where B is a constant.For satisfying the additional requirement that $0 \le \zeta \le 1$, μ_i and w_{ij} must be bounded and positive. A satisfactory choice is

$$0 \le \mu_i \le 1 \; and \; 0 \le w_{ij} \le 1 \; and \; B = 1;$$

For instance,

$$w_{ij} = \frac{\exp(\alpha' Y_{ij})}{1 + \exp(\alpha' Y_{ij})}$$

and $\mu_i = \dfrac{\exp(\beta_i)}{1 + \exp(\beta_i)}$.

Establishment and Application of a Type of Digital Medical Decision-making Optimization Model in the Generalized Information Measurement Space

Supposing { $S_1, S_2, \cdots, S_n$ }is a disease group of information resource and there are n types of in-compatible diseases in this group. Thus, according to Shannon's theory of statistical information, we define the entropy of the disease group (Y)

as $H(Y) = -\sum_{j=1}^{n} P(S_j)\log P(S_j)$, and $P(S_j)$ is the fore probability of disease S_j , $0 < P(S_j) < 1$ and $\sum_{j=1}^{n} P(S_j) = 1$.

Let's assume that we have independently done r items of diagnosis: $v_1, v_2, \cdots, v_i$. We can get m_r incompatible symptoms from examination $K_r\,(1 \le R \le i)$ and K_{ri} is one of them. Now, the doctor's uncertainty of the diagnosis to his patient will reduce from $H(Y)$ to $H(Y \mid K_{ri}) = -\sum_{j=1}^{n} P(S_j \mid K_{ri})\log p(S_j \mid K_{ri}) \cdots (1),$

$r = 1,2,\cdots,i; i = 1,2,\cdots,m_r$, where $P(S_j \mid K_{ri})$ is conditional probability of disease S_j on the condition that symptom V_{ri} has been known. If we define $T(Y, K_{ri}) = H(Y) - H(Y \mid K_{ri}) \cdots (2)$, then $T(Y, K_{ri})$ is the amount of reduction of the disease's uncertainty when K_{ri} is known, namely, the amount of information which the doctor can get .

If the occurrence probability of symptom K_{ri} is $P(K_{ri})$, then the average uncertainty of disease which the doctor can get from examination K_r is

$$H(Y \mid K_r) = \sum_{i=1}^{n_r} P(K_{ri})H(Y \mid K_{ri}) \cdots (3),$$

$r = 1,2,\cdots,i$ and the amount of information is $T(Y,K_r) = H(Y) - H(Y \mid K_r) \cdots (4), r = 1,2,\cdots,i$.

So, we can use formula（1）or（2）to assess the diagnostic value of each symptom and use formula (3) or (4) to assess the diagnostic value of each examination.

$$H_j(K_{ri}) = -P(Y_j \mid K_{ri})\log(Y_j \mid K_{ri}) \cdots (5)$$

, $j = 1, 2 \cdots, n$ shows the partial uncertainty of disease Y_j on the condition that symptom is K_{ri} and the whole uncertainty is $H(Y \mid K_{ri})$. If we have done i items of examination independently, the sum of partial uncertainty of disease Y_j is

$H_i = \sum_{r=1}^{i} H_j(K_{ri}) \quad j = 1, 2, \cdots, n$, ,

$If\ \{H = \min H_j, j = 1, 2, \cdots, n\} \cdots (6)$. Then we can diagnose the patient with the disease $Y_j (1 \le j \le n)$.

APPLICATION PROSPECTS

In today's information age, digitization and networking have penetrated into all sectors and fields of science, technology and national economy. Many information management and decision-making issues can be handled smoothly and effectively by relying on information provided by computer information systems. Artificial intelligence and the computer-aided system also provide a new generation of knowledge processing technology for the sustainable development strategy of modern science and technology, and a large amount of external information can also be queried through the global Internet [Ruan, et. al., 2012]. However, in terms of the nature of information decision-making, computers are not omnipotent. Modern information decision-making is often unruly due to its forward-looking and extremely strategic nature, and requires in-depth analysis and creative thinking to conduct in-depth analysis of all information in order to provide more creative strategic decisions [Shi, et. al., 2008]. With the progress of society and the continuous development of science and technology, modern statistical optimization analysis and intelligent optimization algorithms for big data processing will increasingly show their important role in modern information decision-making [Yang, et. al., 2011]. In fact, in many fields of economy and technology, engineering, and artificial intelligence, without scientific decision-making, it is impossible to achieve sustainable development [Zhang, et. al., 2010].

With the help of information theory and modern statistical optimization analysis, big data analysis and intelligent optimization algorithms, this paper proposes an information method of statistical analysis, which is not only an extension of traditional information statistical methods, but also an extension of classical information theory. The statistical information optimization model for survival life analysis and disease diagnosis proposed in the article on the basis of information entropy is intended to attract the attention of interested experts in the same field.

The 21st century is an information age of cross-integration of multidisciplinary knowledge centered on information technology, big data and intelligent computing technology, computer science. New requirements produce new methods, and new models produce new breakthroughs. Big data statistical optimization analysis and intelligent optimization algorithms understand neurocomputing and life sciences from a new perspective, which greatly strengthens the interaction between mathematics, computing science and life sciences [George, et. al., 2000]. Penetration and connection have greatly accelerated the research process of modern life science and neurocomputing science, and its application scope and application effect are significant.

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