# Optimal Sequential Tests which minimize the Average Sample Size 

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#### Abstract

For testing a hypothesis $H: \theta=\theta_{1}$, vs $A: \theta=\theta_{2}$ ( $\theta_{1}<\theta_{2}$ ), we obtain a truncated sequential bayes procedure which minimizes the average sample size between $\theta_{1}$ and $\theta_{2}$.


## 1. Introduction

Let $X_{1}, X_{2}, \ldots$ be a sequence of random variables (not necessary idd) with joint distribution depending on a real parameter $\theta \in \Theta$. Let $X=\left(X_{1}, X_{2}, \ldots, X_{n}\right)$ at $x^{n}=\left(x_{1}, x_{2}, \ldots, x_{n}\right)$ have a density $P_{n, \theta}\left(x^{n}\right.$ w.r.t. $\mu_{n}\left(d x^{n}\right)$. Now suppose $\theta=\theta_{1}$ is to be tested against $\theta=\theta_{2}$ where $\theta_{1}<\theta_{2}$. Let the error probabilities of any test $\delta$ be $\alpha_{i}(\delta)=P_{\theta_{i}}\left(\delta\right.$ reject $\left.\theta_{i}\right), i=1,2$. Then we can find examples that $E_{\theta} N$ for SPRT(Sequential Probability Ratio Test) is everywhere less than the sample size for fixed sample size procedure having the same $\alpha_{i}(i=1,2)$ and also there are examples that $\max _{\theta_{1} \leq \theta \leq \theta_{2}} E_{\theta} N$ for SPRT is large than the sample size for fixed sample size procedure with the same $\alpha_{i}(i=1,2)$. So there naturally arised the problem to find a procedure which minimizes $\max E_{\theta} N$.

By the optimum properties of the SPRT, given a SPRT $\delta_{0}$ with stopping bounds ( $B, A$ ), $(B \leq 1 \leq A)$ and given $\lambda=\left(\lambda^{1}, \lambda^{2}\right)$ with $0<\lambda^{i}<1(i=1,2)$, the SPRT $\delta_{0}$ is the sequential Bayes procedure $\left(\lambda_{1}, \iota_{1}, \iota_{2}\right)$ for some $\iota_{1}, \iota_{2}>0$. Therefore we can restricted the procedures in the sequential Bayes procedures and furthermore if a sequential Bayes procedure is truncated, then we can easily find the sequential Bayes procedure using the method of backward induction.

Several studies were done trying to minimize $\max _{\theta_{1} \leq \theta_{0} \leq \theta_{2}} E_{\theta} N$. In this paper, we are interested in minimizing the average sample size between $\theta_{1}$ and $\theta_{2}$ instead of minimizing $\max _{\theta} E_{\theta} N$. Throughout this

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paper, let $\left(\mathfrak{X}, \mathfrak{A}, P_{\boldsymbol{\theta}}: \theta \in \Theta\right)$ be a probability space where $\Theta \subset R$ and let $\lambda$ be a prior distribution on $(\Theta, \boldsymbol{B})$ where $\boldsymbol{B}$ is a $\sigma$-field on $\Theta$. We use the following notations;
$\mathfrak{A}$ : actions space, $L: \Theta \times \mathfrak{A} \rightarrow R$ nonnegative finite loss functionn, $\mathfrak{D}: \mathfrak{X} \rightarrow \mathfrak{A}$ the set of decision functions. $R_{\delta}($ or $R(\delta, \lambda))$; the Bayes Risk of $\delta \in \mathfrak{D}$.

## 2. Sequential Bayes procedures

Lemma 1. Let $P=\left\{P_{\theta}: \theta \in \Theta\right\}$ be a dominated family of probability distribution over $(\mathfrak{X}, \mathfrak{A})$. For testing the hypothesis $H: \theta=\theta_{1}$ vs $A: \theta=\theta_{2}\left(\theta_{1}<\theta_{2}\right)$, put $\alpha_{i}(\delta)=P_{\theta_{i}}$ (take wrong decision $\left.\mid \delta\right)$ $i=1,2$ and put $\nu(\delta)=E_{\theta_{0}}(N \mid \delta)$ for some $\theta_{1}<\theta_{0}<\theta_{2}$. Then for a given $0<\alpha_{i}<1, i=1,2$, there is a sequential Bayes procedure $\delta_{\lambda}$ having $\alpha_{i}\left(\delta_{\lambda}\right)=\alpha_{i}(i=1,2)$ which minimizes $\nu(\delta)$ among all procedures $\delta \in \mathfrak{D}$ with $\alpha_{i}(\delta) \leq \alpha_{i}, i=1,2$.

Proof: Let $\lambda=\left(\lambda^{1}, \lambda^{0}, \lambda^{2}\right)$ be a prior distribution on $\left\{\theta_{1}, \theta_{0}, \theta_{2}\right\}$ with $\lambda^{i}>0, i=0,1,2$. Let

$$
L\left(\theta_{i}, a_{j}\right)= \begin{cases}0 & \text { if } i=0 \text { or } i=j, a_{j} \in \mathfrak{D} \\ 1 & \text { otherwise }\end{cases}
$$

and let the cost per observation be constant, say $c>0$ if $\theta=\theta_{0}$ and $c=0$ if $\theta=\theta_{1}$ or $\theta=\theta_{2}$.

$$
R(\delta, \lambda)=\lambda^{1} \alpha_{1}(\delta)+\lambda^{2} \alpha_{2}(\delta)+\lambda^{0} c \nu(\delta) \quad \forall \delta \in \mathfrak{D}
$$

Since $\delta_{\lambda}$ is Bayes $(\lambda), R(\delta, \lambda) \geq R\left(\delta_{\lambda}, \lambda\right) \forall \delta \in \mathfrak{D}$. Therefore $\lambda^{0} c[\nu(\delta)-$ $\left.\nu\left(\delta_{\lambda}\right)\right] \geq \sum_{i=1}^{2} \lambda^{i}\left[\alpha_{i}\left(\delta_{\lambda}\right)-\alpha_{i}(\delta)\right] \geq 0$. So $\min _{\delta \in \mathfrak{D}} \nu(\delta)=\nu\left(\delta_{\lambda}\right)$.

Theorem 2. Let $\left(X_{1}, X_{2}, \ldots, X_{n}\right)$ have a p.d.f. $P_{n, \theta_{i}}\left(x^{n}\right)$ w.r.t $\mu_{n}\left(x^{n}\right)$ under $\theta_{i} \in \Theta$ and $P_{n, \theta_{i}}\left(x^{n}\right) \ll P_{n, \theta_{0}}\left(x^{n}\right) \forall n, i=1,2$. Let $\lambda=\left(\lambda^{1}, \lambda^{0}, \lambda^{2}\right)$ be a prior distribution on $\left\{\theta_{1}, \theta_{0}, \theta_{2}\right\}$ with $\lambda^{i}>0$, $i=0,1,2$. If there exists a converging to zero sequence of constants $\left\{b_{n}^{0}\right\}$ such that $\sum_{i=1}^{2} \lambda^{i} L\left(\theta_{i}, d_{n}^{0}\left(x^{n}\right)\right) P_{n, \theta_{i}}\left(x^{n}\right) / P_{n, \theta_{0}}\left(x^{n}\right) \leq b_{n}^{0}$ where $d_{n}^{0}\left(x^{n}\right)$ is chosen to minimize $\sum_{i=1}^{2} \lambda^{i} L\left(\theta_{i}, d_{n}\left(x^{n}\right)\right) P_{n, \theta_{i}}\left(x^{n}\right)$ among all
$d_{n}\left(x^{n}\right)$. Then the sequential Bayes procedure $\delta_{\lambda}$ to test $\theta=\theta_{1}$ vs $\theta_{2}$ is truncated.

Proof: Let cost per observation be $c(>0)$ if $\theta=\theta_{0}$ and zero if $\theta=\theta_{1}$ or $\theta_{2}$ and let $L\left(\theta_{i}, a_{j}\right)=0$ if $i=0$ or $i=j$ and equals to one otherwise where $a_{j}$ is the action to accept $\theta_{j}$. Define the stopping rule as $\left\{\alpha_{0}, \alpha_{1}\left(x^{1}\right), \alpha_{2}\left(x^{2}\right), \ldots\right\}$ s.t. $\sum_{0}^{\infty} \alpha_{n}(\omega)=1$ where $\omega=\left(x_{1}, x_{2}, \ldots\right)$ and terminal decision rule $\left\{d_{n}\left(x^{n}\right)\right\}$ values in $\left\{a_{1}, a_{2}\right\}$. Then for $d_{n}=$ $d_{n}\left(x^{n}\right)=d_{n}^{0}$,

$$
\begin{aligned}
R(\delta, \lambda)= & \sum_{n=0}^{\infty} \int \alpha_{n}\left(x^{n}\right)\left[\lambda^{0} n c \cdot P_{n_{0}}\left(x^{n}\right)\right. \\
& \left.+\sum_{i=1}^{2} \lambda^{i} L\left(\theta_{i}, d_{n}^{0}\right) P_{n, \theta_{i}}\left(x^{n}\right)\right] \mu_{n}\left(d x^{n}\right) \\
= & \sum_{n=0}^{\infty} \int \alpha_{n}\left(x^{n}\right)\left[\lambda^{0} n c+b_{n}\left(x^{n}\right)\right] P_{n, \theta_{0}}\left(x^{n}\right) \mu_{n}\left(d x^{n}\right) \\
= & \sum_{n=0}^{\infty} E_{\theta_{0}} \alpha_{n}\left(\lambda^{n}\right)\left[\lambda^{0} n c+b_{n}\left(X^{n}\right)\right]
\end{aligned}
$$

where $\left.b_{n}\left(x^{n}\right)=\sum_{i=1}^{2} \lambda^{i} L\left(\theta_{i}, d_{n}^{0}\right) P_{n, \theta_{i}}\left(x^{n}\right) / P_{n, \theta_{0}} \neq x^{n}\right)$. Put

$$
E_{\theta_{0}} \alpha_{n}\left(X^{n}\right) b_{n}\left(X^{n}\right) / E_{\theta_{0}} \alpha_{n}\left(X^{n}\right) \equiv \bar{b}_{n}
$$

then $\bar{b}_{n} \leq b_{n}^{0} \forall n$. We have $R(\delta, \lambda)=\sum_{n=0}^{\infty} E_{\theta_{0}} \alpha_{n}\left(X^{n}\right)\left[\lambda^{0} n c+\bar{b}_{n}\right]=$ $\sum_{n=0}^{\infty} \beta_{n}\left(\lambda^{0} n c+\bar{b}_{n}\right)$ where $\beta_{n}=E_{\theta_{0}} \alpha_{n}\left(X^{n}\right)$. Let $n_{0}$ be s.t. $b_{n}^{0}<\lambda^{0} c$ for all $n \geq n_{0}$. Then the sequential Bayes procedure $\delta_{\lambda}$ must have $\beta_{n}=0$ for $n>n_{0}$. So $\alpha_{n}\left(x^{n}\right)=0$ a.e. $P_{\theta_{0}}$, so does a.e. $P_{\theta_{i}}$.

Theorem 3. Let $\left\{X_{i}\right\}$ be a sequence of random variables defined on ( $\mathfrak{X}, \mathfrak{A}, P_{\theta}, \theta \in \Theta \subset R$ ) and let $X^{n}=\left(X_{1}, X_{2}, \ldots, X_{n}\right)$ have a p.d.f. $P_{n, \theta}\left(x^{n}\right)$ w.r.t $\mu_{n}\left(d x^{n}\right)$ at $x^{n}=\left(x_{1}, x_{2}, \ldots, x_{n}\right)$. For testing $H: \theta=\theta_{1}$ vs $A: \theta=\theta_{2}\left(\theta_{1}<\theta_{2}\right)$ with error probabilities $\alpha_{i}$ $\left(0<\alpha_{i}<1\right) i=1,2$.

If there is a sequence of constants $\left\{b_{n}^{0}\right\}$ with $b_{n}^{0} \rightarrow 0$ as $n \rightarrow \infty$ such that $\min _{i} P_{n, \theta_{i}}\left(x^{n}\right) \cdot\left(\theta_{2}-\theta_{1}\right) / \int_{\theta_{1}}^{\theta_{2}} P_{n, \theta}\left(x^{n}\right) d \theta \leq b_{n}^{0} \forall n$. Then there is a truncated sequential Bayes procedure $\delta_{\lambda}$ such that $\int_{\theta_{1}}^{\theta_{2}} E_{\theta}\left(N \mid \delta_{\lambda}\right) d \theta=$ $\min _{\delta \in \mathfrak{D}} \int_{\theta_{1}}^{\theta_{2}} E_{\theta}(N \mid \delta) d \theta$ for all $\alpha_{i}(\delta)=P_{\theta}\left(\delta\right.$ reject $\left.\theta_{i}\right) \leq \alpha_{i}, i=1,2$.

Proof: Define a prior distribution on $\Theta$ as follows; $\lambda\left(\theta_{i}\right)=\lambda^{i}>0$, $i=1,2, \lambda=0$ if $\theta<\theta_{1}$ or $\theta>\theta_{2}$ and $\lambda^{0} d \theta$ on interval $\left(\theta_{1}, \theta_{2}\right)$ with $\lambda^{1}+\lambda^{2}+\lambda^{0}\left(\theta_{2}-\theta_{1}\right)=1$. Assume that the loss equals to one for wrong terminal decision, and cost per observation equals to one for each $\theta$, $\theta_{1}<\theta<\theta_{2}$ but no cost if $\theta=\theta_{1}$ or $\theta_{2}$. Let $\left\{\alpha_{n}\right\}$ be a sequence of stopping rule. Then

$$
\begin{aligned}
R(\delta, \lambda)= & \sum_{n=0}^{\infty} \alpha_{n}\left(x^{n}\right) \int\left\{\sum_{i=1}^{2} \lambda^{i} L\left(\theta_{i}, d_{n}\left(x^{n}\right)\right) P_{n, \theta_{i}}\left(x^{n}\right)\right. \\
& \left.+n \lambda^{0} \int_{\theta_{1}}^{\theta^{2}} P_{n, \theta}\left(x^{n}\right) d \theta\right\} \mu_{n}\left(d x^{n}\right)
\end{aligned}
$$

Observe that the best determinal decision $d_{n}\left(x^{n}\right)=\theta_{1}$ if $\lambda^{1} P_{n, \theta_{1}}\left(x^{n}\right)>$ $\lambda^{2} P_{n, \theta_{2}}\left(x^{n}\right)$, and equals to $\theta_{2}$ if $\lambda^{1} P_{n, \theta_{1}}\left(x^{n}\right)<\lambda^{2}$. $P_{n, \theta_{2}}\left(x^{n}\right)$. So for best decision rule $R(\delta, \lambda)=\sum_{n=0}^{\infty} \alpha_{n}\left(x^{n}\right) \int\left\{\min _{i} \lambda^{i} \cdot P_{n, \theta_{i}}\left(x^{n}\right)+\right.$ $\left.n \lambda^{0} \int_{\theta_{1}}^{\theta_{2}} P_{n, \theta}\left(x^{n}\right) d \theta\right\} \mu_{n}\left(d x^{n}\right)$. Let $\bar{P}_{n}\left(x^{n}\right)=\frac{1}{\theta_{2}-\theta_{1}} \int_{\theta_{1}}^{\theta_{2}} P_{n, \theta}\left(x^{n}\right) d \theta$, then $\bar{P}_{n}\left(x^{n}\right)$ is a density w.r.t $\mu_{n}\left(d x^{n}\right)$ and

$$
\begin{aligned}
R(\delta, \lambda)= & \sum_{n=0}^{\infty} \alpha_{n}\left(x^{n}\right) \int \bar{P}_{n}\left(x^{n}\right)\left\{n\left(\theta_{2}-\theta_{1}\right) \lambda^{0}\right. \\
& \left.+\min _{i} \lambda^{i} P_{n, \theta_{i}}\left(x^{n}\right) / \bar{P}_{n}\left(x^{n}\right)\right\} \mu_{n}\left(d x^{n}\right)
\end{aligned}
$$

Since $\min _{i} P_{n, \theta_{i}}\left(x^{n}\right) / \bar{P}_{n}\left(x^{n}\right) \leq b_{n}^{0}$ which converges to zero, there exists a truncated sequential Bayes procedure $\delta_{\lambda}$ which minimizes the average sample size by the theorem 2.

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