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of two survival curves under
proportional hazards model**

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CONFIDENCE BANDS FOR THE DIFFERENCE OF TWO SURVIVAL FUNCTIONS UNDER PROPORTIONAL HAZARDS MODEL

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Astract.

A common approach to testing for differences between the survival rates of two therapies is to use a proportional hazards regression model which allows for an adjustment of the two survival functions for any imbalance in prognostic factors in the comparison. An alternative approach to this problem is to plot the difference between the two predicted survival functions with a confidence band that provides information about when these two treatments differ. Such a band will depend on the covariate values of a given patient. In this paper we show how to construct a confidence band for the difference of two survival functions based on the proportional hazards model. A simulation approach is used to generate the bands. This approach is used to compare the survival probabilities of chemotherapy and allogeneic bone marrow transplants for chronic leukemia.

1. Introduction

A common problem encountered in biomedical applications is the comparison of the survival rates of two treatments. In this comparison one tests the two treatments against a common survival function or equivalently the same hazard function over a given time period. When there are additional covariates associated with survival, the testing is typically performed in the framework of a Cox (1972) proportional hazards model.

When the testing results indicate that the two survival functions are different, patients and physicians often want to know “at what times are the two treatments different?”. This is

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plots and comparing their confidence bands. In this section we summarize the different methods for comparing two survival functions. Recently, Parzen *et al.* (1997) used the Kaplan-Meier (1958) estimators of two survival functions, $\hat{F}_1(\cdot)$ and $\hat{F}_2(\cdot)$, to estimate the difference between two survival functions and they proposed a simulation method to construct a confidence band for the difference.

In many applications there is a need, when comparing two treatments, to make adjust-

Here, β can be estimated by maximizing the stratified Cox partial log likelihood function

$$C(\beta, t) = \sum_{i=1}^2 \sum_{j=1}^{n_i} \int_0^t \beta' Z_{ij} d_{ij}(u) - \sum_{i=1}^2 \int_0^t \log \left(\sum_{j=1}^{n_i} Y_{ij}(u) e^{\beta' Z_{ij}} \right) d_{i^-}(u),$$

where $d_{ij}(u) = I\{X_{ij} \leq T_{ij} \leq u, D_{ij} = 1\}$, $d_{i^-} = \sum_i d_{ij}$, and $Y_{ij}(u) = I\{X_{ij} \leq u \leq T_{ij}\}$ is the indicator of the i th j th individual is at risk at time u and is in the i th treatment group. Note that an individual is at risk only since its own truncation time, so that the size of the risk set is initially increasing and then decreasing.

To compare the predicted survival curves, we estimate the conditional survival functions for the two treatments for a patient with a particular set of covariates z_0 ,

$$F_i(t; z_0) = P(T > t | z_0, \text{Treatment } i) = e^{-\Lambda_i(t; z_0)},$$

where $\Lambda_i(t; z_0) = e^{\beta' z_0} \int_0^t \lambda_{i0}(u) du$. An estimator of the cumulative baseline hazard rate for treatment i , $i = 1, 2$ is given by Breslow's (1975) estimator

$$\hat{\Lambda}_{i0}(t) = \int_0^t \frac{d_{i^-}(u)}{\sum_{j=1}^{n_i} Y_{ij}(u) \exp(\hat{\beta}' Z_{ij})}.$$

For convenience, we introduce the notations

$$\begin{aligned} S_i^{(k)}(\beta, t) &= \frac{1}{n_i} \sum_{j=1}^{n_i} Y_{ij}(t) Z_{ij}^{\otimes k} e^{\beta' Z_{ij}}, \\ \bar{S}_i(\beta, t) &= S_i^{(1)}(\beta, t) / S_i^{(0)}(\beta, t), \\ V_i(\beta, t) &= S_i^{(2)}(\beta, t) / S_i^{(0)}(\beta, t) - \bar{S}_i(\beta, t), \\ s_i^{(k)}(\beta, t) &= \{S_i^{(k)}(\beta, t)\}, \\ e_i(\beta, t) &= s_i^{(1)}(\beta, t) / s_i^{(0)}(\beta, t), \\ v_i(\beta, t) &= s_i^{(2)}(\beta, t) / s_i^{(0)}(\beta, t) - e_i(\beta, t), \end{aligned}$$

for $i = 1, 2$, and $k = 0, 1, 2$, where for a column vector a , $a^{\otimes 0} = 1$, $a^{\otimes 1} = a$, and $a^{\otimes 2} = aa'$.

For simplicity of presentation, we assume $\{X_{ij}, T_{ij}, D_{ij}, Z_{ij}\}$, ($j = 1, \dots, n_i$) are independent and identically distributed, $P(T_{ij} \geq X_{ij}) > 0$, and $\{Z_{ij}\}$ is bounded. Left-truncated and right-censored survival data as been studied extensively. The more general conditions required to obtain large sample results for this type of data can be found in Woodroof (1985), Lai and Ying (1991) and Andersen *et al.* (1993). Andersen *et al.* (1993) argued that the martingale central limit theory can be applied to left-truncated data, so that the asymptotic results based on right-censored data can be extended to left-truncated and right-censored data. Also we assume that the two samples are independent. Let $n = n_1 + n_2$. Then, if $n_i/n \rightarrow p_i > 0$, for $i = 1, 2$, $\hat{\beta}$ is a consistent estimator of β , and

$$\sqrt{n}(\hat{\beta} - \beta) \xrightarrow{\mathcal{D}} (0, \Sigma^{-1}),$$

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$$\Sigma = \sum_{i=1}^2 p_i \int_0^{\infty} v_i(\beta, t) s^{(0)}(\beta, t) \lambda_{i0}(t) dt,$$

ic is assumed to be positive definite and can be consistently estimated by the observed information matrix

$$\hat{\Sigma} = \mathbf{1}$$

It follows that the variance of $W(t; z_0)$

The transplant cohort included 548 patients receiving hydroxyurea or interferon α -trastuzumab and a HLA-identical sibling bone marrow transplant (BMT). All patients were reported to the International Bone Marrow Transplant Registry (IBMTR). IBMTR is a voluntary working group of over 30 transplant centers worldwide that contribute data on their allogeneic bone marrow transplants to a Statistical Center at the Medical College of Wisconsin. Patients in this arm were diagnosed between 1983 and 1991, and were between 15 and 55 years of age. For detailed patient characteristics see Gal *et al* [3].

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Figure 1a shows estimated survival curves for a recently diagnosed (≥ 1988) older (≥ 35 years) male patient with large spleen size ≥ 1 cm. Figure 1b shows estimated difference (BMT-mortality) based on total survival curves with a 95% point estimate confidence interval and 95% confidence band for such a patient. A similar plot for a patient diagnosed prior to 1988 with the same characteristics is given in Figure 2.

These confidence band plots indicated that the mortality treatment as an early survival advantage, perhaps, to the toxicity of the bone marrow transplant. There is a significant late survival advantage for transplant patient due to a longer relapse rate. Also for the recently treated cases (Figure 1) BMT had a survival advantage (95% confidence band is > 0) starting at 5.5 years after diagnosis. This is in contrast to patients treated prior to 1988 (Figure 2) where BMT started to show an advantage only after 8.29 years since diagnosis. This may be due to the improvement of bone marrow transplant techniques over the years.

In this example, there are 16 sets of possible covariate values. The time points since diagnosis where BMT starts to have a survival advantage are presented in Table 2. The time points ranged from 5.5 years to 8.29 years since diagnosis depending on the given patient characteristics. By contrast to the comparison of the Kaplan-Meier survival curves, this comparison of the predicted survival curves based on the Cox model provides more information to both physicians and patients.

Table 2. Time points t_0 since diagnosis (DX) in years where BMT starts to have survival advantage.

Sex	Covariate Values			C_α	t_0
	Spleen Size	Age	Year of DX		
M	< 1 cm	< 35	< 88	2.96	7.84
M	< 1 cm	< 35	≥ 88	2.97	5.97
M	≥ 1 cm	< 35	< 88	2.96	7.84
M	≥ 1 cm	< 35	≥ 88	2.99	5.88
M	< 1 cm	≥ 35	< 88	2.99	7.84
M	< 1 cm	≥ 35	≥ 88	2.95	5.88
M	≥ 1 cm	≥ 35	< 88	2.96	8.29
M	≥ 1 cm	≥ 35	≥ 88	2.94	5.5
F	< 1 cm	< 35	< 88	2.96	8.29
F	< 1 cm	< 35	≥ 88	2.93	5.97
F	≥ 1 cm	< 35	< 88	2.99	7.84
F	≥ 1 cm	< 35	≥ 88	2.98	6.24
F	< 1 cm	≥ 35	< 88	2.92	7.84
F	< 1 cm	≥ 35	≥ 88	2.89	5.97
F	≥ 1 cm	≥ 35	< 88	2.9	7.84
F	≥ 1 cm	≥ 35	≥ 88	2.92	5.88

References

Plotting the confidence band for the difference of two predicted survival functions provides a valuable decision making tool for physicians and patients. The proposed simulation method is easy to program, and offers a flexible way to construct such confidence bands, particularly when limiting distributions cannot be evaluated analytically. The proposed simulation method can be extended to compare the difference of two survival curves based on other models, such as Aalen's (1989) additive model or other more general models.

The estimated critical value, C_α , depends on the number of replications. It is important to know what is the appropriate. In our example for an early diagnosed young (< 35 yr) male patient with small spleen size (< 1 cm), the estimated C'_α 's are 3.1, 2.98, 2.97, 3.1, 2.97, and 3.1 for $n = 5, 15, 3, 5, 8$ and 1, respectively. It appears that the estimate of C_α is reasonably stable after only 5 replications.

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