Supply Forecasting via Survival Curve Estimation

Gary D. Knott, Ph.D.

Civilized Software Inc. 12109 Heritage Park Circle Silver Spring, MD 20906 USA email:csi@civilized.com URL:www.civilized.com Tel: (301) 962-3711

Suppose we have "shelf-life" data for a group of n items. These items might be automobiles, or laser printer toner cartridges, or vials of vaccine, or entry-slots for admission to a course. In the case of a physical item which is to be replaced as it is "consumed", we are interested in forecasting the nature and rate of consumption, and in estimating a suitable replacement schedule. This is an important component of planning and managing the supply-logistics for the items of interest.

Suppose, that for most items, we have the age of the item when it was "consumed", *i.e.* removed from our group of items; this age is the "shelf-life" of that item; generally this age is called the *survival time* of the item. However, let us also suppose we may have *censoring* present; that is, for some consumed items, we do not have the exact survival time, *i.e.* the exact age at consumption, but only an age for the item such that at some unknown time *after* this age, the item was consumed. In this case, the actual survival time has been "censored", *i.e.* hidden from our view. This kind of complication might arise when, for example, incomplete records are kept, or when dates of consumption are not recorded consistently, but periodic inventory data is available.

Our data thus consists of pairs of values $(y_1, e_1), (y_2, e_2), \ldots, (y_n, e_n)$ where each e_i is either 0 or 1. When $e_i = 1, y_i$ is the survival time until the consumption of item *i*, counting from the study starting point, and when $e_i = 0, y_i$ is the censoring time for item *i*, indicating that item *i* was lost to follow-up with an unknown consumption time sometime after y_i time-units from the study starting point. The value e_i is called the result-code for item *i*.

Suppose the items in the group being studied have survival times, X_1 , X_2, \ldots, X_n , which are independent identically-distributed random variables, a realization of which is, except for censoring, given by our data. Let F(t) be the common distribution function of X_1, \ldots, X_n . We wish to estimate the survival function $S(t) = P(X_i > t) = 1 - F(t)$.

Associated with each X_i , we postulate a censoring-time random variable, C_i . The random variables C_1, \ldots, C_n are assumed to be independent and identically-distributed, with the distribution function $G(t) = P(C_i \leq t)$. For any realization, $(\tilde{X}_i, \tilde{C}_i)$ where \tilde{X}_i is a sample of X_i and \tilde{C}_i is a sample of C_i , if $\tilde{X}_i \leq \tilde{C}_i$, we have $y_i = \tilde{X}_i$, and $e_i = 1$, while when $\tilde{X}_i > \tilde{C}_i$, we have $y_i = \tilde{C}_I$ and $e_i = 0$. Thus, the value y_i is a sample of $\min(X_i, C_i)$.

If we assume a specific formula for the censoring-time distribution function G(t), then we can estimate S(t) by (1 - H(t))/(1 - G(t)) where H(t)is the empirical cumulative distribution function of the data-values y_1, \ldots, y_n . It is appropriate to adjust this estimate to be monotonically-decreasing and to smooth it to obtain the final estimate. For example, suppose the censoring-time distribution is uniform on the interval [0, 4]; then, given the column vector Y listed below, where Y_i holds the observed survival time y_i , we can estimate the survival function S in MLAB with the function SEgiven below, and then monotonize, smooth, and graph it. The actual resultcode vector, E, associated with this data is listed below together with Y for later reference, even though E is not needed to be used in the parametric estimating function SE.

* TYPE Y&'E

MATRIX : 1.635686 0 .3113416 0 .4963642 1 1.131409 0 2.221448 0 1.668752 1 2.785097 0

.3379156	0
.4495545	1
3.020983	1
.3994093	0
.9359379	1
.9697097	0
.6193121	0
.1234482	0
.8931070	1
.2233199	1
.8303535	0
3.926499	0
2.012626	1
.3871494	1
.9381460	1
1.210837	1
1.704919	0
1.006140	1
1.998524	1
.3763392	0
1.184550	0
.7832847	1
.9971150	0
.0452861	0
2.145687	1
.8396369	1
1.319498	0
3.288359	1
.7552886	1
1.017174	0
.8238844	1
.5893285	1
.2916714	0
3.266290	0
2.215458	1
.5546782	0
.1355474	1
.1247086	0
.9045237	1
.4080161	1

- 1.188316 1
- 1.243582 1
- 1.043640 1
- * L = 4
- * H = CDF(Y)
- * FUNCTION SE(T)=IF T>=L THEN 0 ELSE (1-LOOKUP(h,t))/(1-T/L)
- * DRAW SMOOTHSPLINE(MONOT(POINTS(SE,0:L:.1), -1), 0:L!140)
- * top title "Survival function estimate via (1-cdf(y))/(1-G)"
- * VIEW



We can avoid assuming a specific censoring-time distribution by using the asymptotically-unbiased Kaplan-Meier product-limit estimator function, \hat{S} as the estimator function for the survival function S. This can be computed in MLAB using the KMSURV function and graphed using the STEPGRAPH function.

For example, given the data vector, Y, listed above, together with the associated result-code vector, E, we can produce a graph of our estimated survival curve \tilde{S} as shown below. The tic-marks show the points where censored observations occur.

* DELETE W



We may postulate a specific form for the distribution of the X_i random variables. For example, if the survival time distribution function is a Weibull distribution with group-specific parameters, a and b, then the survival curve is given by $SW(t) = exp(-(t/a)^b)$.

Now, we may estimate the parameters a and b using MLAB to fit the model function SW(t) to a matrix of points lying on the Kaplan-Meier estimated survival curve. This is demonstrated for the matrix H1 of points

on the estimated survival curve obtained above. Greenwood's variance approximation for \hat{S} computed by KMSURV() in H1 col 3 is used to compute appropriate weights for the curve-fit.

```
* FUNCTION SW(T)=EXP(-((IF T=0 THEN .000001 ELSE T)/A)^B)
* A = 1;B = 1; H1[1,3] = 1
* FIT(A,B), SW TO H1 COL 1:2 WITH WEIGHT 1/(H1 COL 3)
final parameter values
   value
                                       dependency
                                                      parameter
                    error
    1.837800012
                   0.05250877741
                                      0.3849266596
                                                      А
                   0.05755968774
    1.451240067
                                      0.3849266596
                                                      В
4 iterations
CONVERGED
best weighted sum of squares = 8.691990e+00
weighted root mean square error = 5.673848e-01
weighted deviation fraction = 1.869069e-02
R \text{ squared} = 9.756895e-01
* DRAW POINTS(SW,0:4:.05)
* bottom title "Fit of Weibull distribution to Kaplan-Meier curve"
* view
```



Sometimes we may wish to compare the survival curves of several dis-

similar groups of items, to determine, for example, which of several distinct marketing strategies is superior. This can be done by comparing the estimated survival curves directly with an appropriate statistical test (such as the Mantel-Haensel test, MHT) provided by MLAB.

It may be of interest to compute the expected survival time of an item that has already survived k time-units, *i.e.* has not been consumed by time k. This is just $M(k) := \int_k^\infty tq(t|k) dt$, where q(t|k) is the conditional density function, $d[P(X_1 \ge t|X_1 \ge k)]/dt$. But given the survial time distribution function F and the corresponding density function f(t) = dF(t)/dt, we can compute q(t|k) = if t < k then 0 else f(t)/a, where

$$a = \int_{k}^{\infty} f(s) \, ds = 1 - F(k) = S(k).$$

Note q(t|0) = 0 and q(t|t) is just the hazard function f(t)/S(t).

The expected additional survival time function M(k) can be easily computed and graphed in MLAB. One use for the function M(k) is to estimate lifetimes for items with censored survival times. By thus "completing" a data set, we obtain uncensored data which is amenable to a variety of otherwise inapplicable statistical procedures.

Now we may suppose we have a survival function s(t), possibly obtained by curve-fitting observed survival data, that describes the survival time characteristics of the items of interest. Thus, we assume we have the survival function s, where s(t) is the fraction of items which survive at least to time t. Suppose that we wish to replace these items on a regular schedule so as to maintain the constant level of a_0 items available. It is reasonable to assume that each newly-introduced replacement batch of items follows the same survival behavior as the original items. We wish to compute the replacement schedule function. Note the replacement function can be used for budget projection purposes.

Here we shall look at the discrete formulation of the problem where time is measured in discrete increments as an integer value of say, hours, days or weeks. Set $s_0 = 1$ and in general let s_i be the fraction of items which survive for at least *i* weeks. Let a_0 be the initial number of items at time 0, and let a_i denote the number of items available at the beginning of week *i*. Then the number of these items available at the start of week *k* is $a_0s_k + a_1s_{k-1} + \cdots + a_ks_0$. Since we wish to maintain the constant level of a_0 items at each week, we equate a_0 and $a_0s_k + a_1s_{k-1} + \cdots + a_ks_0$. From this we get the following recursion equation for a_k , $0 \le k$.

$$a_k = (a_0 - \sum_{j=1}^{k-1} a_j s_{k-j})/s_0$$

with a_0 and s_0, s_1, \ldots, s_k given.

This represents the solution vector of the following lower-triangular Toeplitz system.

$\begin{bmatrix} s_0 \\ s_1 \\ \vdots \end{bmatrix}$	$egin{array}{c} 0 \ s_0 \ s_1 \end{array}$	$egin{array}{c} 0 \ 0 \ s_0 \end{array}$	0 0 :	$\begin{bmatrix} a_0\\a_1\\\cdot \end{bmatrix}$	=	$\left[\begin{array}{c}a_0\\a_0\\\cdot\end{array}\right]$	
s_k	\vdots s_{k-1}		s_0	a_k		$\begin{bmatrix} : \\ a_0 \end{bmatrix}$	

The MLAB function DECONV may be used to compute the solution to this linear system.

For example, here is the replacement schedule function computed by using **DECONV** based on the best-fitting Weibull survival curve for the data above. Note the first point indicates we obtain the entire initial group of items at once (100 percent). Note also that the replacement schedule curve rapidly converges to a nearly-constant replacement amount per week.



replacement schedule curve for the fit survival curve

In practice, we should re-estimate our survival curve and replacement schedule curve from time to time, so that changes in consumption do not invalidate the resupply process.