Survival Analysis: Time To Event Modelling

Sudipta Das

Assistant Professor,
Department of Computer Science,
Ramakrishna Mission Vivekananda Educational & Research Institute

Outline I

1. Non Parametric Estimation

Non Parametric Estimation: Introduction I

- In this section, we shall examine techniques for drawing an inference about the distribution of the time to some event X, based on a sample of *right-censored survival data.*
- We assume that the potential censoring time is unrelated to the potential event time.
  - This assumption would be violated, for example, if patients with poor prognosis were routinely censored.
- The methods are appropriate for Type I, Type II, progressive or random censoring.

Non Parametric Estimation: Introduction II

- Notations:
  - Suppose that the events occur at D distinct times

$$0 = t_0 \leq t_1 < t_2 < \ldots < t_D < \infty$$

  - Let d_i be the number of events occur at time t_i.
    - Events are sometimes simply referred to as deaths
  - Let Y_i be the number of individuals who are at risk at time t_i.
    - Note that Y_i is a count of the number of individuals with a time on study of t_i or more
    - Equivalently, this is the number of individuals who are alive at t_i or experience the event of interest at t_i

Non Parametric Estimation: Introduction III

- Objective: To model the time to event/ survival time (T) by
  - Modeling the survival function

$$S(t) = P(T > t)$$

  - Modeling the cumulative hazard function

$$H(t) = \int_0^t \frac{f(u)}{P(T > u)} du$$

- Note: We are not assuming any structural form for the survival time distribution

Modeling Survival Function I

- **Kaplan-Meier estimator** to model/estimate the survival function

$$
\begin{aligned}
\hat{S}(t) &= \prod_{t_i \le t,\ i=1}^{n} \left(1 - \frac{d_i}{Y_i}\right)^{\delta_i} \\
&= \prod_{i:\ t_i \le t} \left(\frac{Y_i - d_i}{Y_i}\right)
\end{aligned}
$$

  - $d_i =$ Number of failured/death at t_i
  - $Y_i =$ Number at risk of dying or failure at t_i
  - $\delta_i = \begin{cases} 1 & \text{if } t_i \text{ is observed failure,} \\ 0 & \text{if } t_i \text{ is censoring time.} \end{cases}$
  - Product of conditional survivals

Modeling Survival Function II

- Example: Consider the data on the time to relapse of patients in a clinical trial of 6-MP against a placebo. We shall consider only the 6-MP patients.

$$6, 6, 6, 6+, 7, 9+, 10, 10+, 11+, 13, 16, 17+,$$

$$19+, 20+, 22, 23, 25+, 32+, 32+, 34+, 35+$$

Modeling Survival Function III

Table: Construction of the Product-Limit Estimator for the 6-MP Group

Time t_i	Number of events d_i	Number at risk Y_i	KM estimate $\hat{S}(t) = \prod_{t_i \leq t} \left(1 - \frac{d_i}{Y_i}\right)$
6	3	21	$\left[1 - \frac{3}{21}\right] = 0.857$
7	1	17	$0.857 \times \left[1 - \frac{1}{17}\right] = 0.807$
10	1	15	$0.807 \times \left[1 - \frac{1}{15}\right] = 0.753$
13	1	12	$0.753 \times \left[1 - \frac{1}{12}\right] = 0.690$
16	1	11	$0.690 \times \left[1 - \frac{1}{11}\right] = 0.628$
22	1	7	$0.628 \times \left[1 - \frac{1}{7}\right] = 0.538$
23	1	6	$0.538 \times \left[1 - \frac{1}{6}\right] = 0.448$

Modeling Survival Function IV

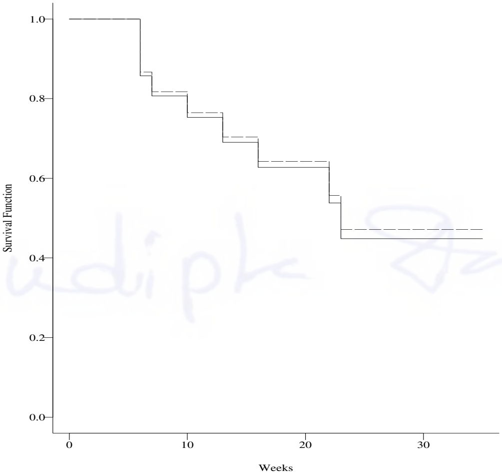

Figure 4.1A *Comparison of the Nelson–Aalen (------) and Product-Limit (————) estimates of the survival function for the 6-MP group.*

Modeling Survival Function V

- The Product-Limit estimator was constructed by using a reduced-sample approach.
- In this approach, note that, because events are only observed at the times t_i,
  - $S(t)$ should be a step function with jumps only at these times,
  - there being no information on events occurring at other times.
- We will estimate $S(t)$ by a discrete distribution with mass at the time points $t_1, t_2, \ldots, t_D$.

Modeling Survival Function VI

- We can estimate the $Pr[T > t_i | T \geq t_i]$ as the fraction of individuals who are at risk at time t_i but who do not die at this time, that is

$$\begin{aligned} \hat{Pr}[T > t_i | T \geq t_i] &= \frac{Y_i - d_i}{Y_i}, \text{ for } i = 1, 2, \ldots, D. \\ &= 1 - \frac{d_i}{Y_i} \\ &= 1 - \hat{Pr}[T = t_i | T \geq t_i] \end{aligned}$$

Modeling Survival Function VII

- To estimate $S(t_i)$, recall that

$$
\begin{aligned}
S(t_i) &= \frac{S(t_i)}{S(t_{i-1})} \times \frac{S(t_{i-1})}{S(t_{i-2})} \times \cdots \times \frac{S(t_2)}{S(t_1)} \times \frac{S(t_1)}{S(t_0)} \times S(t_0) \\
&= P[T > t_i | T > t_{i-1}] \times P[T > t_{i-1} | T > t_{i-2}] \cdots P[T > t_2 | T > t_1] \times P[T > t_1 | T > t_0] \times 1 \\
&= P[T > t_i | T \geq t_i] \times P[T > t_{i-1} | T \geq t_{i-1}] \cdots P[T > t_2 | T \geq t_2] \times P[T > t_1 | T \geq t_1]
\end{aligned}
$$

- Thus,

$$
\hat{S}(t) = \prod_{i:\ t_i \leq t} \left(\frac{Y_i - d_i}{Y_i} \right)
$$

Modeling Survival Function VIII

- **Kaplan-Meier estimator**
  - It is also known as product-limit estimator
  - It can be shown to be nonparametric MLE of survival function, under certain regularity conditions
  - In the absence of censoring, it reduces to complement of the *empirical distribution function* (EDF):

$$\hat{S}(t) = 1 - \frac{\text{Number of obs } \leq t}{\text{Total Number of obs}}$$

Modeling Survival Function IX

- Kaplan-Meier estimators of either the survival function or the cumulative hazard rate are consistent.
- For values of t beyond the largest observation time this estimator is not well defined
  - Efron (1967) suggests estimating $\hat{S}(t)$ by 0 for $t > t_{\max}$. (This leads to a negatively biased estimator)
  - Gill (1980) suggests estimating $\hat{S}(t)$ by $\hat{S}(t_{\max})$ for $t > t_{\max}$. (This leads to a positively biased estimator)
  - Although both estimators have the same large-sample properties and converge to the true survival function for large samples

Modeling Survival Function X

- Variance of KM Estimate (Greenwood's formula):

$$\hat{Var}(\hat{S}(t)) = \hat{S}^2(t) \sum_{i:t_i \le t} \frac{d_i}{Y_i(Y_i - d_i)}$$
$$= \hat{S}^2(t)\sigma_S^2(t),$$

where $\sigma_S^2(t) = \sum_{i:t_i \le t} \frac{d_i}{Y_i(Y_i - d_i)}$

  - It underestimate the true variance of the Kaplan-Meier estimator for small to moderate samples.

Table: Construction of the variance of KM Estimator for the 6-MP Group

Time t_i	# of events d_i	# at risk Y_i	KM est. $\hat{S}(t)$	$\sigma^2_S(t) = \sum_{t_i \le t} \frac{d_i}{Y_i(Y_i - d_i)}$	Variance of $\hat{S}(t)$ $\hat{V}(\hat{S}(t)) = \hat{S}^2(t) \sum_{t_i \le t} \frac{d_i}{Y_i(Y_i - d_i)}$
6	3	21	0.857	$\frac{3}{21 \times 18} = 0.0079$	$0.857^2 \times 0.0079 = 0.0058$
7	1	17	0.807	$0.0079 + \frac{1}{17 \times 16} = 0.0116$	$0.807^2 \times 0.0116 = 0.0076$
10	1	15	0.753	$0.0116 + \frac{1}{15 \times 14} = 0.0164$	$0.753^2 \times 0.0164 = 0.0093$
13	1	12	0.690	$0.0164 + \frac{1}{12 \times 11} = 0.0240$	$0.690^2 \times 0.0240 = 0.0114$
16	1	11	0.628	$0.0240 + \frac{1}{11 \times 10} = 0.0330$	$0.628^2 \times 0.0330 = 0.0130$
22	1	7	0.538	$0.0330 + \frac{1}{7 \times 6} = 0.0569$	$0.538^2 \times 0.0569 = 0.0164$
23	1	6	0.448	$0.0569 + \frac{1}{6 \times 5} = 0.0902$	$0.448^2 \times 0.0902 = 0.0181$

Modeling Survival Function XII

- The variance was constructed by the help of delta method.
- Recall that

$$\hat{S}(t_i) = \prod_{j=1}^{i} \left[\frac{Y_j - d_j}{Y_j} \right] = \prod_{j=1}^{i} \hat{p}_j$$

- Thus,

$$\log \left[\hat{S}(t_i) \right] = \sum_{j=1}^{i} \log \left[\hat{p}_j \right]$$

Modeling Survival Function XIII

- Hence,

$$
\begin{aligned}
\hat{Var}\left[\log\left[\hat{S}(t_i)\right]\right] &= \sum_{j=1}^{i} \hat{Var}\left\{\log\left[\hat{p}_j\right]\right\} \\
&= \sum_{j=1}^{i} \left[\hat{p}_j\right]^{-1} \left\{\hat{Var}\left[\hat{p}_j\right]\right\} \left[\hat{p}_j\right]^{-1} \\
&= \sum_{j=1}^{i} \left[\hat{p}_j\right]^{-2} \left\{\frac{\hat{p}_j\left[1-\hat{p}_j\right]}{Y_j}\right\} \\
&= \sum_{j=1}^{i} \left[\hat{p}_j\right]^{-1} \left[1-\hat{p}_j\right] \frac{1}{Y_j} \\
&= \sum_{j=1}^{i} \left[\frac{Y_j-d_j}{Y_j}\right]^{-1} \left[\frac{d_j}{Y_j}\right] \frac{1}{Y_j} = \sum_{j=1}^{i} \frac{d_j}{Y_j(Y_j-d_j)}
\end{aligned}
$$

- Therefore,

$$\begin{aligned}
\hat{Var}\left[\hat{S}(t_i)\right] &= \hat{Var}\left[e^{\log\left[\hat{S}(t_i)\right]}\right] \\
&= \left[e^{\log\left[\hat{S}(t_i)\right]}\right] \hat{Var}\left[\log\left[\hat{S}(t_i)\right]\right] \left[e^{\log\left[\hat{S}(t_i)\right]}\right] \\
&= \left[\hat{S}(t_i)\right]^2 \sum_{j=1}^{i} \frac{d_j}{Y_j(Y_j - d_j)}
\end{aligned}$$

- And

$$\hat{Var}\left[\hat{S}(t)\right] = \left[\hat{S}(t)\right]^2 \sum_{i:t_i \leq t} \frac{d_i}{Y_i(Y_i - d_i)}$$

Modeling Survival Function XV

- Standard error of KM Estimate:

$$\hat{SE}(\hat{S}(t)) = \hat{S}(t)\sqrt{\sum_{t_i \le t} \frac{d_i}{Y_i(Y_i - d_i)}}$$

- Asymptotic property of KM Estimate
  - Under suitable regularity conditions, the Product-Limit estimator converges weakly to Gaussian process.
  - This fact means that for fixed t, the estimator has an approximate normal distribution.

Modeling Survival Function XVI

- Thus, the $100(1-\alpha)\%$ *point-wise* Confidence Interval of $S(t)$:

$$\left[\hat{S}(t) - z_{1-\alpha/2} \times \hat{SE}(\hat{S}(t)), \hat{S}(t) + z_{1-\alpha/2} \times \hat{SE}(\hat{S}(t))\right] \tag{1}$$

  - Called linear confidence interval
  - Appropriate for large sample

Modeling Survival Function XVII

Table: The Product-Limit Estimator and Its Estimated Standard Error for the 6-MP Group

Time on Study t	KM Estimator $\hat{S}(t)$	Standard Error $\hat{SE}(\hat{S}(t))$	95% CI
$0 \leq t < 6$	1.000	0.000	$[1, 1]$
$6 \leq t < 7$	0.857	0.076	$[0.708, 1.006]$
$7 \leq t < 10$	0.807	0.087	$[0.636, 0.978]$
$10 \leq t < 13$	0.753	0.096	$[0.565, 0.941]$
$13 \leq t < 16$	0.690	0.107	$[0.480, 0.900]$
$16 \leq t < 22$	0.628	0.114	$[0.405, 0.851]$
$22 \leq t < 23$	0.538	0.128	$[0.287, 0.789]$
$23 \leq t < 35$	0.448	0.135	$[0.183, 0.713]$

Modeling Cumulative Hazard Function from Survival Function

- Cumulative Hazard Function $H(t)$ can be constructed from Survival Function $S(t)$
  - Cumulative Hazard Function:

$$\hat{H}(t) = -\log \hat{S}(t)$$

  - $(1-\alpha)100\%$ Confidence Interval:

$$-\log\left[\hat{S}(t) \pm z_{1-\alpha/2} \times \sqrt{\hat{Var}(\hat{S}(t))}\right]$$

Modeling Cumulative Hazard Function I

- **Nelson-Aalen estimator** to model/estimate the cumulative hazard function
$$\tilde{H}(t) = \sum_{i:\ t_i \le t} \frac{d_i}{Y_i}.$$
    - d_i = Number of failured/death at t_i
    - Y_i = number at risk of dying or failure at t_i
- Its variance
$$\hat{Var}(\tilde{H}(t)) = \sum_{t_i \le t} \frac{d_i}{Y_i^2} = \sigma_H^2(t).$$

Modeling Cumulative Hazard Function II

Table: Construction of the variance of Nelson–Aalen Estimator for the 6-MP Group

Time t_i	# of events d_i	# at risk Y_i	Nalson-Aalen estimator $\tilde{H}(t)=\sum_{t_i\leq t}\frac{d_i}{Y_i}$	Variance of $\tilde{H}(t)$ $\sigma^2_H(t)=\hat{V}(\tilde{H}(t))=\sum_{t_i\leq t}\frac{d_i}{Y_i^2}$
6	3	21	$\frac{3}{21}=0.1428$	$\frac{3}{21^2}=0.0068$
7	1	17	$0.1428+\frac{1}{17}=0.2017$	$0.0068+\frac{1}{17^2}=0.0103$
10	1	15	$0.2017+\frac{1}{15}=0.2683$	$0.0103+\frac{1}{15^2}=0.0147$
13	1	12	$0.2683+\frac{1}{12}=0.3517$	$0.0147+\frac{1}{12^2}=0.0217$
16	1	11	$0.3517+\frac{1}{11}=0.4426$	$0.0217+\frac{1}{11^2}=0.0299$
22	1	7	$0.4426+\frac{1}{7}=0.5854$	$0.0299+\frac{1}{7^2}=0.0503$
23	1	6	$0.5854+\frac{1}{6}=0.7521$	$0.0503+\frac{1}{6^2}=0.0781$

Modeling Cumulative Hazard Function III

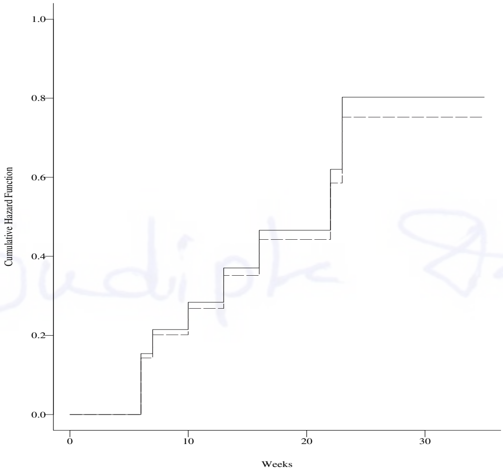

Figure 4.1B *Comparison of the Nelson–Aalen (------) and Product-Limit (———) estimates of the cumulative hazard rate for the 6-MP group.*

Modeling Cumulative Hazard Function IV

- Note
  - The Nelson-Aalen estimator of the cumulative hazard rate is the first term in a Taylor series expansion of minus the logarithm of the Product-Limit estimator.
  - Under certain regularity conditions, one can show that the Nelson-Aalen estimator is nonparametric maximum likelihood estimator.
  - Nelson-Aalen estimators of either the survival function or the cumulative hazard rate are consistent.

Modeling Cumulative Hazard Function V

- Standard error of NA estimator:

$$\hat{SE}(\tilde{H}(t)) = \sqrt{\sum_{t_i \leq t} \frac{d_i}{Y_i^2}} = \sigma_H(t).$$

- Asymptotic property of NA Estimate
  - Under suitable regularity conditions, the Nelson-Aalen estimator converges weakly to Gaussian process.
  - This fact means that for fixed t, the estimator has an approximate normal distribution.
- Thus, the $100(1-\alpha)\%$ Confidence Interval of $H(t)$:

$$\left[\tilde{H}(t) - z_{1-\frac{\alpha}{2}} \times \hat{SE}(\tilde{H}(t)), \tilde{H}(t) + z_{1-\frac{\alpha}{2}} \times \hat{SE}(\tilde{H}(t))\right]$$

Modeling Cumulative Hazard Function VI

Table: The Nelson-Aalen Estimator, Its estimated standard error and 95% CI for the 6-MP Group

Time on Study t	NA Estimator $\tilde{H}(t)$	Standard Error $\hat{SE}(\tilde{H}(t))$	95% CI
$0 \leq t < 6$	0.0000	0.0000	$[1, 1]$
$6 \leq t < 7$	0.1428	0.0068	$[0.1295, 0.1561]$
$7 \leq t < 10$	0.2017	0.0103	$[0.1815, 0.2219]$
$10 \leq t < 13$	0.2683	0.0147	$[0.2395, 0.2971]$
$13 \leq t < 16$	0.3517	0.0217	$[0.3092, 0.3943]$
$16 \leq t < 22$	0.4426	0.0299	$[0.3840, 0.5012]$
$22 \leq t < 23$	0.5854	0.0503	$[0.4868, 0.6840]$
$23 \leq t < 35$	0.7521	0.0781	$[0.5990, 0.9052]$

Modeling Survival Function from Cumulative Hazard Function

- Survival Function $S(t)$ can be constructed from Cumulative Hazard Function $H(t)$
  - Survival Function:
$$\tilde{S}(t) = e^{-\tilde{H}(t)}$$
  - $(1 - \alpha)100\%$ Confidence Interval:
$$e^{-\tilde{H}(t) \pm z_{1-\alpha/2} \times \sqrt{\hat{Var}(\tilde{H}(t))}}$$

Non Parametric Estimation: Example in R

- Example: Bank Credit Data
  - Data read
  - Data preparation
  - Kaplan-Meier Estimator/ Product Limit Estimator for Survival Function
    - **FIGURE 5A**
  - Nelson-Aalen Estimator for Cumulative Hazard Function
    - **FIGURE 5B**
  - Nelson-Aalen Estimator for Survival Function
    - **FIGURE 5C**

Hazard Rate Estimation I

- The Nelson-Aalen estimator $\tilde{H}(t)$, provides an efficient means of estimating the cumulative hazard function $H(t)$.
- In most applications, the parameter of interest is not $H(t)$, but rather its derivative $h(t)$, the hazard rate.
- However, the slope of the Nelson-Aalen estimator provides a crude estimate of the hazard rate $h(t)$.
- Here, we shall discuss the use of kernel smoothing technique to estimate $h(t)$.

Hazard Rate Estimation II

- Recall that, $\tilde{H}(t)$ is a step function with jumps at the event times, $0 = t_0 < t_1 < t_2 < \cdots < t_D$.
- Let
$$\Delta\tilde{H}(t_i) = \tilde{H}(t_i) - \tilde{H}(t_{i-1})$$
and
$$\Delta\hat{V}[\tilde{H}(t_i)] = \hat{V}[\tilde{H}(t_i)] - \hat{V}[\tilde{H}(t_{i-1})]$$
denote the magnitude of the jumps in $\tilde{H}(t_i)$ and $\hat{V}[\tilde{H}(t_i)]$ at time t_i.
- However, $\Delta\tilde{H}(t_i)$ provides a crude estimator of $h(t)$ at the death times.

Hazard Rate Estimation III

- The kernel-smoothed estimator of $h(t)$ is a weighted average of these crude estimates over event times close to t.
    - Closeness is determined by a bandwidth b, so that event times in the range $t - b$ to $t + b$ are included in the weighted average which estimates $h(t)$.
    - The bandwidth b is chosen either to minimize some measure of the mean-squared error or to give a desired degree of smoothness.
- The weights are controlled by the choice of a kernel function, $K(\cdot)$, which determines how much weight is given to points at a distance from t.

Hazard Rate Estimation IV

- Common choices for the kernel are the
  - Uniform kernel with

$$K(x) = \frac{1}{2}, \text{ for } -1 \leq x \leq 1$$

  - Epanechnikov kernel with

$$K(x) = 0.75(1 - x^2), \text{ for } -1 \leq x \leq 1$$

  - Biweight kernel with

$$K(x) = \frac{15}{16}(1 - x^2)^2, \text{ for } -1 \leq x \leq 1$$

Hazard Rate Estimation V

- The kernel-smoothed hazard rate estimator of $h(t)$ based on the kernel $K(\cdot)$
  - for time points $b \leq t \leq t_D - b$,

$$\hat{h}(t) = b^{-1} \sum_{i=1}^{D} K\left(\frac{t - t_i}{b}\right) \Delta \tilde{H}(t_i) \tag{2}$$

- its variance

$$\sigma^2[\hat{h}(t)] = b^{-2} \sum_{i=1}^{D} K\left(\frac{t - t_i}{b}\right)^2 \Delta \hat{V}\left[\tilde{H}(t_i)\right] \tag{3}$$

Hazard Rate Estimation VI

- for time points $0 < t < b$, kernel $K(x)$ modified as
  - Uniform kernel

$$K_q(x) = \frac{4(1+q^3)}{(1+q)^4} + \frac{6(1-q)}{(1+q)^3}x, \text{ for } -1 \leq x \leq q,$$

  where $q = t/b$
  - Epanechnikov kernel

$$K_q(x) = K(x)(\alpha_E + \beta_E x), \text{ for } -1 \leq x \leq q,$$

  where $\alpha_E = \frac{64(2-4q+6q^2-3q^3)}{(1+q)^4(19-18q+3q^2)}$ and $\beta_E = \frac{240(1-q)^2}{(1+q)^4(19-18q+3q^2)}$
  - Biweight kernel

$$K_q(x) = K(x)(\alpha_{BW} + \beta_{BW} x), \text{ for } -1 \leq x \leq q,$$

  where $\alpha_{BW} = \frac{64(8-24q+48q^2-45q^3+15q^4)}{(1+q)^5(81-168q+126q^2-40q^3+5q^4)}$ and
  $\beta_{BW} = \frac{1120(1-q)^3}{(1+q)^5(81-168q+126q^2-40q^3+5q^4)}$

Hazard Rate Estimation VII

- for time points $t_D - b < t < t_D$, kernel $K(x)$ modified as
  - Uniform kernel
    $$K_q(x) = \frac{4(1+q^3)}{(1+q)^4} - \frac{6(1-q)}{(1+q)^3}x, \text{ for } -q \le x \le 1,$$
    where $q = (t_D - t)/b$
  - Epanechnikov kernel
    $$K_q(x) = K(-x)(\alpha_E - \beta_E x), \text{ for } -q \le x \le 1,$$
    where $\alpha_E = \frac{64(2-4q+6q^2-3q^3)}{(1+q)^4(19-18q+3q^2)}$ and $\beta_E = \frac{240(1-q)^2}{(1+q)^4(19-18q+3q^2)}$
  - Biweight kernel
    $$K_q(x) = K(-x)(\alpha_{BW} - \beta_{BW} x), \text{ for } -q \le x \le 1,$$
    where $\alpha_{BW} = \frac{64(8-24q+48q^2-45q^3+15q^4)}{(1+q)^5(81-168q+126q^2-40q^3+5q^4)}$ and
    $\beta_{BW} = \frac{1120(1-q)^3}{(1+q)^5(81-168q+126q^2-40q^3+5q^4)}$

Hazard Rate Estimation VIII

- The estimated, smoothed, hazard rate and its variance are given by (2) and (3), respectively, using the kernel K_q.
- See Example 6.1 at page 168.
- Confidence intervals or confidence bands for the hazard rate, based on the smoothed hazard rate estimate, can be constructed similarly to those for the cumulative hazard rate discussed earlier.

Hazard Rate Estimation IX

- *Note:-* One must be very careful in interpreting the kernel-smoothed estimates constructed by these techniques.
    - What these statistics are estimating is not the hazard rate $h(t)$, but rather a smoothed version of the hazard rate

$$h^*(t) = b^{-1} \int K\left(\frac{t-u}{b}\right) h(u)du$$

    - The confidence interval formula is, in fact, a confidence interval for h^*

Hazard Rate Estimation X

- *Note:-* The estimate depends on both the bandwidth b and the kernel used in estimation.
- Bandwidth b is chosen in such a way that the mean integrated squared error ($MISE$) of $\hat{h}$ over the range t_L to t_U defined by

$$MISE(b) = E\int_{t_L}^{t_U}\left(\hat{h}(u) - h(u)\right)^2 du = E\int_{t_L}^{t_U}\hat{h}^2(u)du - 2E\int_{t_L}^{t_U}\hat{h}(u)h(u)du + E\int_{t_L}^{t_U}h^2(u)du$$

  is minimized.
  - The first term is estimated as $\int_{t_L}^{t_U}\hat{h}^2(u)du$. This integral is further approximated by the trapezoid rule.
  - The second term is estimated by a cross-validation estimate suggested by Ramlau-Hansen.
  - The last term is independent of the choice of the kernel and the bandwidth and can be ignored when finding the best value of b.

Hazard Rate Estimation XI

- Thus, In the reality, an estimated function of $MISE(b)$ defined as below

$$g(b)=\sum_{i=1}^{M-1}\left[\frac{u_{i+1}-u_i}{2}\right]\left[\hat{h}^2(u_{i+1})+\hat{h}^2(u_i)\right]-\frac{2}{b}\sum_{i\neq j}K\left(\frac{t_i-t_j}{b}\right)\Delta\tilde{H}(t_i)\Delta\tilde{H}(t_j)$$

  is minimized over b to choose the optimal bandwidth b.
- A small bandwidth produces a small bias term, but a large variance term, whereas the reverse holds for a large bandwidth.
  - The optimal bandwidth is a trade-off between the two terms.