STAT 661: Project LS v.s. EM

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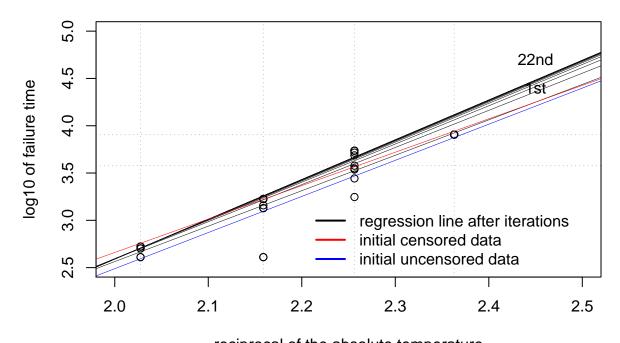
1 Appendix

1.1 Least Square Method with Full data

Using Schmee & Hahn's Least Square method, we reproduced the algoritm and got the exact same results after 22 iterations. The results of $\hat{\beta}_0, \hat{\beta}_1$, and $\hat{\sigma}$ are -5.8181182, 4.2041845, 0.2043471.

In page 422, The authors say "If one ignores the 150c data, the iterative least squares estimates and the maximum likelihood estimates were even closer to each other than before". I will try to confirm this concultion.

Least Squares Method with full data



| Iteration | Intercept | Slope | Sigma | mu150 | mu170 | mu190 | mu220 |
|-----------|-----------|----------|-----------|----------|----------|----------|----------|
| 1 | -4.930507 | 3.747043 | 0.1572178 | 4.038379 | 3.808887 | 3.329470 | 2.829844 |
| 2 | -5.260094 | 3.926205 | 0.1798671 | 4.098530 | 3.839728 | 3.365551 | 2.858422 |
| 3 | -5.485695 | 4.040237 | 0.1910656 | 4.130648 | 3.855994 | 3.381991 | 2.869259 |
| 4 | -5.622963 | 4.108341 | 0.1968923 | 4.148614 | 3.864902 | 3.390365 | 2.874186 |
| 5 | -5.704072 | 4.148284 | 0.2000799 | 4.158863 | 3.869919 | 3.394903 | 2.876685 |
| 6 | -5.751540 | 4.171581 | 0.2018782 | 4.164772 | 3.872793 | 3.397450 | 2.878038 |
| 7 | -5.779242 | 4.185155 | 0.2029105 | 4.168199 | 3.874456 | 3.398907 | 2.878799 |
| 8 | -5.795405 | 4.193069 | 0.2035086 | 4.170195 | 3.875424 | 3.399750 | 2.879235 |
| 9 | -5.804842 | 4.197688 | 0.2038570 | 4.171359 | 3.875988 | 3.400240 | 2.879488 |
| 10 | -5.810356 | 4.200386 | 0.2040605 | 4.172040 | 3.876318 | 3.400526 | 2.879636 |
| 11 | -5.813580 | 4.201964 | 0.2041795 | 4.172438 | 3.876511 | 3.400694 | 2.879722 |
| 12 | -5.815466 | 4.202887 | 0.2042491 | 4.172671 | 3.876624 | 3.400791 | 2.879772 |
| 13 | -5.816571 | 4.203427 | 0.2042899 | 4.172807 | 3.876690 | 3.400849 | 2.879802 |
| 14 | -5.817217 | 4.203743 | 0.2043138 | 4.172887 | 3.876729 | 3.400882 | 2.879819 |
| 15 | -5.817596 | 4.203929 | 0.2043278 | 4.172934 | 3.876752 | 3.400902 | 2.879829 |
| 16 | -5.817817 | 4.204037 | 0.2043359 | 4.172961 | 3.876765 | 3.400913 | 2.879835 |
| 17 | -5.817947 | 4.204101 | 0.2043407 | 4.172977 | 3.876773 | 3.400920 | 2.879838 |
| 18 | -5.818023 | 4.204138 | 0.2043436 | 4.172987 | 3.876777 | 3.400924 | 2.879840 |
| 19 | -5.818068 | 4.204160 | 0.2043452 | 4.172992 | 3.876780 | 3.400927 | 2.879842 |
| 20 | -5.818094 | 4.204173 | 0.2043462 | 4.172995 | 3.876782 | 3.400928 | 2.879842 |
| 21 | -5.818109 | 4.204180 | 0.2043467 | 4.172997 | 3.876783 | 3.400929 | 2.879843 |
| 22 | -5.818118 | 4.204185 | 0.2043471 | 4.172998 | 3.876783 | 3.400929 | 2.879843 |
| NA | NA | NA | NA | NA | NA | NA | NA |

1.2 Removing 150c

After removing the 150c censored data and 16 iterations, the results of $\hat{\beta}_0, \hat{\beta}_1, \hat{\sigma}$ are -4.6042301, 3.6366424, 0.2410175. From the figure and table we can know the estimats of $\hat{\beta}_1$ and log time to failure are smaller.

However, the censored data are underestimated values. After iterations, we anticipate the estimate should be larger than the before.

The reason might be below:

For the full data, the initial total fitted $\hat{\beta}_1$ (3.747043) is lager than the $\hat{\beta}_1$ (3.532411) fitted merely by censored data. The positive difference will be accumulated during the iterations and make the $\hat{\beta}_1$ and $\hat{\mu}$ larger and larger until convergency.

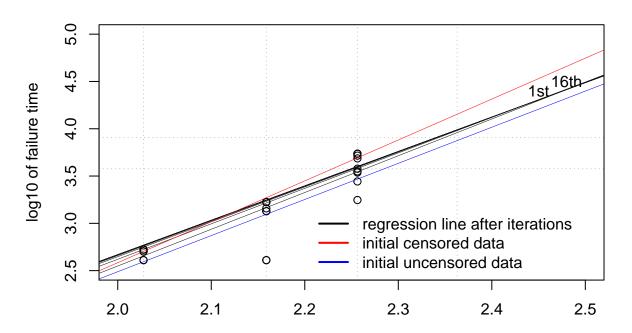
Without the 150c data, the initial total fitted $\hat{\beta}_1$ (3.886073) is smaller than the $\hat{\beta}_1$ (4.324944) fitted merely by censored data. Thus, the negative difference will be accumulated during the iterations and make the $\hat{\beta}_1$ and $\hat{\mu}$ smaller and smaller.

| | fit0.coef | fit_c.coef | fit0_no150.coef | fit_c_no150.coef |
|-------------|-----------|------------|-----------------|------------------|
| (Intercept) | -4.930507 | -4.404674 | -5.223416 | -6.066011 |
| X | 3.747043 | 3.532411 | 3.886073 | 4.324944 |
| | | | | |

Note:

The initial regression coefficients

LS Method without 150c



reciprocal of the absolute temperature

| Iteration | Intercept | Slope | Sigma | mu170 | mu190 | mu220 |
|-----------|-----------|----------|-----------|----------|----------|----------|
| 1 | -5.223416 | 3.886073 | 0.1822782 | 3.830161 | 3.351240 | 2.846310 |
| 2 | -4.875219 | 3.747684 | 0.2150043 | 3.862018 | 3.393390 | 2.894494 |
| 3 | -4.725422 | 3.686426 | 0.2292010 | 3.875601 | 3.411077 | 2.915461 |
| 4 | -4.659330 | 3.659284 | 0.2355862 | 3.881710 | 3.418975 | 2.924904 |
| 5 | -4.629525 | 3.647036 | 0.2385086 | 3.884509 | 3.422581 | 2.929223 |
| 6 | -4.615901 | 3.641438 | 0.2398561 | 3.885801 | 3.424242 | 2.931214 |
| 7 | -4.609628 | 3.638860 | 0.2404795 | 3.886399 | 3.425010 | 2.932134 |
| 8 | -4.606728 | 3.637669 | 0.2407683 | 3.886676 | 3.425365 | 2.932560 |
| 9 | -4.605385 | 3.637117 | 0.2409022 | 3.886805 | 3.425530 | 2.932758 |
| 10 | -4.604763 | 3.636861 | 0.2409643 | 3.886864 | 3.425607 | 2.932850 |
| 11 | -4.604475 | 3.636743 | 0.2409931 | 3.886892 | 3.425642 | 2.932892 |
| 12 | -4.604341 | 3.636688 | 0.2410065 | 3.886905 | 3.425659 | 2.932912 |
| 13 | -4.604279 | 3.636662 | 0.2410127 | 3.886911 | 3.425666 | 2.932921 |
| 14 | -4.604250 | 3.636650 | 0.2410156 | 3.886913 | 3.425670 | 2.932925 |
| 15 | -4.604236 | 3.636645 | 0.2410169 | 3.886915 | 3.425672 | 2.932927 |
| 16 | -4.604230 | 3.636642 | 0.2410175 | 3.886915 | 3.425672 | 2.932928 |
| NA | NA | NA | NA | NA | NA | NA |

1.3 EM Method with full data

$$\log(f(\beta_0, \beta_1, \sigma | y, z)) = -\frac{n}{2} \ln(2\pi) - n \ln(\sigma) - \frac{1}{2\sigma^2} \sum_{i=1}^{n} (t_i - \beta_0 - \beta_1 \nu_i)^2$$

$$\mu_i = \beta_0 - \beta_1 \nu_i; \ \mu_j = \beta_0 - \beta_1 \nu_j; \ z_i^* = \frac{w_i - \mu_i^*}{\sigma^*}$$

• E-step Let $\vec{\theta} = (\beta_0, \beta_1, \sigma)$

$$E[T_i|T_i > w_i, \vec{\theta}^*] = \mu_i^* + \sigma^* H(\frac{w_i - \mu_i^*}{\sigma^*})$$

$$E[T_i^2 | T_i > w_i, \vec{\theta}^*] = \mu_i^{*2} + \sigma^{*2} + \sigma^*(w_i + \mu_i^*) H(\frac{w_i - \mu_i^*}{\sigma^*})$$

$$E[(T_i - \beta_0 - \beta_1 \nu_i)^2 | T_i > w_i, \vec{\theta}^{\star}] = \mu_i^{\star 2} + \sigma^{\star 2} + \sigma^{\star}(w_i + \mu_i^{\star}) H(\frac{w_i - \mu_i^{\star}}{\sigma^{\star}}) - 2(\beta_0 + \beta_1 \nu_i) [\mu_i^{\star} + \sigma^{\star} H(\frac{w_i - \mu_i^{\star}}{\sigma^{\star}})] + (\beta_0 + \beta_1 \nu_i)^2 H(\frac{w_i - \mu_i^{\star}}{\sigma^{\star}}) + (\beta_0 + \beta_1 \nu_i)^2 H(\frac{w_$$

$$E[(T_i - \mu_i)^2 | T_i > w_i, \vec{\theta}^*] = (\mu_i^* - \mu_i)^2 + \sigma^{*2} + \sigma^* H(z_i^*)(w_i + \mu_i^* - 2\mu_i)$$

$$Q(\vec{\theta}, \vec{\theta}^*) = -\frac{n}{2}\ln(2\pi) - n\ln(\sigma) - \frac{1}{2\sigma^2}\sum_{j=1}^{m}(t_j - \beta_0 - \beta_1\nu_j)^2 - \frac{1}{2\sigma^2}\sum_{i=m+1}^{n}E[(T_i - \beta_0 - \beta_1\nu_i)^2|T_i > w_i, \vec{\theta}^*]$$

$$= -\frac{n}{2}\ln(2\pi) - n\ln(\sigma) - \frac{1}{2\sigma^2}\sum_{i=1}^{m}(t_j - \mu_j)^2 - \frac{1}{2\sigma^2}\sum_{i=m+1}^{n}[(\mu_i^{\star} - \mu_i)^2 + \sigma^{\star 2} + \sigma^{\star}H(z_i^{\star})(w_i + \mu_i^{\star} - 2\mu_i)]$$

• M-step

$$\frac{\partial Q}{\partial \beta_0} = -\frac{1}{\sigma^2} \left\{ \sum_{j=1}^m [t_j - \beta_0 - \beta_1 \nu_j] + \sum_{i=m+1}^n [\mu_i^{\star} + \sigma^{\star} H(\frac{w_i - \mu_i^{\star}}{\sigma^{\star}}) - \beta_0 - \beta_1 \nu_i] \right\} = 0$$

$$n\beta_0 = \sum_{j=1}^m t_j + \sum_{i=m+1}^n [\mu_i^{\star} + \sigma^{\star} H(z_i^{\star})] - \beta_1 n \bar{\nu}$$

$$\frac{\partial Q}{\partial \beta_1} = -\frac{1}{\sigma^2} \left\{ \sum_{j=1}^m [t_j - \beta_0 - \beta_1 \nu_j] \nu_j + \sum_{i=m+1}^n [\mu_i^{\star} + \sigma^{\star} H(\frac{w_i - \mu_i^{\star}}{\sigma^{\star}}) - \beta_0 - \beta_1 \nu_i] \nu_i \right\} = 0$$

$$n\beta_0 \bar{\nu} + \beta_1 \sum_{i=1}^n \nu_i^2 = \sum_{j=1}^m t_j \nu_j + \sum_{i=m+1}^n [\mu_i^{\star} + \sigma^{\star} H(z_i^{\star})] \nu_i$$

$$\beta_1 (\sum_{i=1}^n \nu_i^2 - n \bar{\nu}^2) = \sum_{i=1}^m t_j (\nu_j - \bar{\nu}) + \sum_{i=m+1}^n [\mu_i^{\star} + \sigma^{\star} H(z_i^{\star})] (\nu_i - \bar{\nu})$$

$$\frac{\partial Q}{\partial \sigma^2} = \frac{1}{2\sigma^2} \left\{ -n + \frac{1}{\sigma^2} \sum_{j=1}^m [t_j - \beta_0 - \beta_1 \nu_j]^2 + \frac{1}{\sigma^2} \sum_{i=m+1}^n E[(T_i - \beta_0 - \beta_1 \nu_i)^2 | T_i > w_i, \vec{\theta}^*] \right\} = 0$$

$$\sum_{j=1}^m [t_j - \beta_0 - \beta_1 \nu_j]^2 + \sum_{i=m+1}^n \left\{ \mu_i^{\star 2} + \sigma^{\star 2} + \sigma^{\star} (w_i + \mu_i^{\star} - 2\mu_i) H(\frac{w_i - \mu_i^{\star}}{\sigma^{\star}}) - 2\mu_i \mu_i^{\star} + \mu_i^2 \right\} = n\sigma^2$$

$$\sigma^2 = \frac{1}{n} \sum_{j=1}^m [t_j - \mu_j]^2 + \frac{1}{n} \sum_{i=m+1}^n \left\{ (\mu_i^{\star} - \mu_i)^2 + \sigma^{\star 2} + \sigma^{\star} H(z_i^{\star}) (w_i + \mu_i^{\star} - 2\mu_i) \right\}$$

1.4 the EM algorithm's pseudo code

```
Algorithm 1: EM algorithm
```

```
input : observed data \mathcal{D} = \{\vec{x}_1, \vec{x}_2, \cdots, \vec{x}_N\}, joint distribution P(\vec{x}, \vec{z} | \vec{\theta}) output: model's parameters \vec{\theta}

// 1. identify hidden variables \vec{z}, write out the log likelihood function \ell(\vec{x}, \vec{z} | \vec{\theta})

\vec{\theta}^{(0)} = \dots // initialize

while (!convergency) do

// 2. E-step: plug in P(\vec{x}, \vec{z} | \vec{\theta}), derive the formula of Q(\vec{\theta}, \vec{\theta}^{t-1})

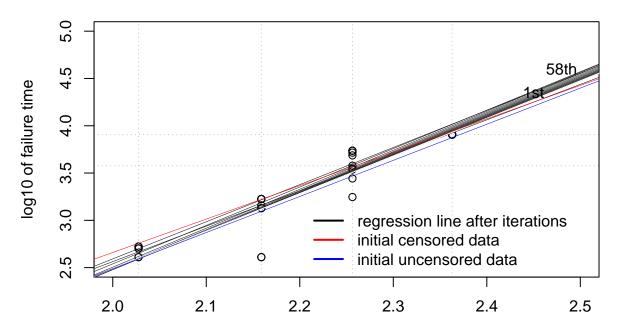
Q(\vec{\theta}, \vec{\theta}^{t-1}) = \mathbb{E}\left[\ell_c(\vec{\theta}) | \mathcal{D}, \theta^{t-1}\right]

// 3. M-step: find \vec{\theta} that maximizes the value of Q(\vec{\theta}, \vec{\theta}^{t-1})

\vec{\theta}^t = \arg\max_{\vec{\theta}} Q(\vec{\theta}, \vec{\theta}^{t-1})
```

Using the EM method, the results of $\hat{\beta}_0, \hat{\beta}_1, \hat{\sigma}$ are -5.4578366, 3.9733333, 0.018129 after 58th iterations. Although the estimates are smaller than SL method, Thay shows a same trend: $\hat{\beta}_1$ and $\hat{\mu}$ grow larger and converges.

EM Method with full data



reciprocal of the absolute temperature

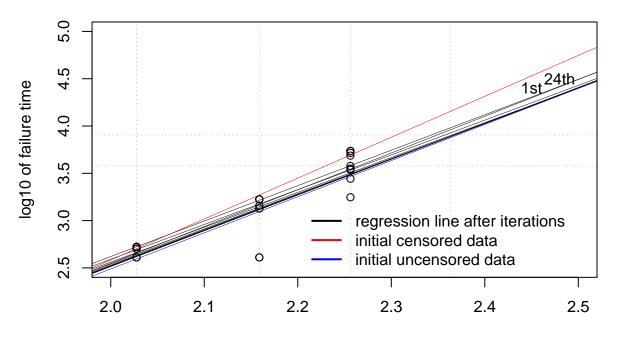
| Iteration | Intercept | Slope | Sigma | mu150 | mu170 | mu190 | mu220 |
|-----------|-----------|----------|-----------|----------|----------|----------|----------|
| 1 | -4.930507 | 3.747043 | 0.1572178 | 4.038379 | 3.808887 | 3.329470 | 2.829844 |
| 2 | -5.260094 | 3.926205 | 0.0449471 | 4.050153 | 3.680115 | 3.264915 | 2.747165 |
| 3 | -5.585591 | 4.062652 | 0.0251975 | 4.032650 | 3.626700 | 3.212574 | 2.677855 |
| 4 | -5.732754 | 4.118786 | 0.0212259 | 4.015227 | 3.598996 | 3.182290 | 2.640391 |
| 5 | -5.770367 | 4.129102 | 0.0197975 | 4.000948 | 3.582072 | 3.165400 | 2.622215 |
| 6 | -5.756341 | 4.118542 | 0.0191495 | 3.989547 | 3.571096 | 3.155924 | 2.614158 |
| 7 | -5.721871 | 4.100219 | 0.0188085 | 3.980474 | 3.563607 | 3.150469 | 2.611124 |
| 8 | -5.682223 | 4.080442 | 0.0186071 | 3.973241 | 3.558265 | 3.147201 | 2.610463 |
| 9 | -5.644265 | 4.061973 | 0.0184778 | 3.967464 | 3.554318 | 3.145146 | 2.610840 |
| 10 | -5.610667 | 4.045825 | 0.0183899 | 3.962841 | 3.551322 | 3.143788 | 2.611606 |
| 48 | -5.457867 | 3.973348 | 0.0181290 | 3.944190 | 3.540117 | 3.139833 | 2.617182 |
| 49 | -5.457860 | 3.973344 | 0.0181290 | 3.944189 | 3.540116 | 3.139833 | 2.617183 |
| 50 | -5.457854 | 3.973342 | 0.0181290 | 3.944189 | 3.540116 | 3.139833 | 2.617183 |
| 51 | -5.457850 | 3.973340 | 0.0181290 | 3.944188 | 3.540116 | 3.139833 | 2.617183 |
| 52 | -5.457846 | 3.973338 | 0.0181290 | 3.944188 | 3.540116 | 3.139833 | 2.617183 |
| 53 | -5.457844 | 3.973336 | 0.0181290 | 3.944187 | 3.540115 | 3.139833 | 2.617183 |
| 54 | -5.457841 | 3.973335 | 0.0181290 | 3.944187 | 3.540115 | 3.139833 | 2.617183 |
| 55 | -5.457839 | 3.973335 | 0.0181290 | 3.944187 | 3.540115 | 3.139833 | 2.617183 |
| 56 | -5.457838 | 3.973334 | 0.0181290 | 3.944187 | 3.540115 | 3.139833 | 2.617184 |
| 57 | -5.457837 | 3.973333 | 0.0181290 | 3.944187 | 3.540115 | 3.139833 | 2.617184 |
| NA | NA | NA | NA | NA | NA | NA | NA |

Note:

The first and last 10 rows

1.5 EM Method removing 150c data

EM Method without 150c



reciprocal of the absolute temperature

| Iteration | Intercept | Slope | Sigma | mu170 | mu190 | mu220 |
|-----------|-----------|----------|-----------|----------|----------|----------|
| 1 | -5.223416 | 3.886073 | 0.1822782 | 3.830161 | 3.351240 | 2.846310 |
| 2 | -4.875219 | 3.747684 | 0.0575427 | 3.670831 | 3.274048 | 2.783605 |
| 3 | -4.762086 | 3.676729 | 0.0331780 | 3.585724 | 3.209264 | 2.727418 |
| 4 | -4.809491 | 3.685452 | 0.0271869 | 3.548621 | 3.174609 | 2.691440 |
| 5 | -4.886346 | 3.714029 | 0.0252545 | 3.533220 | 3.157487 | 2.670509 |
| 6 | -4.947773 | 3.738961 | 0.0245452 | 3.526938 | 3.149167 | 2.658893 |
| 7 | -4.988000 | 3.755853 | 0.0242571 | 3.524372 | 3.145114 | 2.652614 |
| 8 | -5.012002 | 3.766108 | 0.0241305 | 3.523311 | 3.143123 | 2.649273 |
| 9 | -5.025600 | 3.771976 | 0.0240715 | 3.522861 | 3.142135 | 2.647512 |
| 10 | -5.033065 | 3.775218 | 0.0240430 | 3.522666 | 3.141639 | 2.646590 |
| 11 | -5.037083 | 3.776970 | 0.0240289 | 3.522579 | 3.141389 | 2.646109 |
| 12 | -5.039217 | 3.777903 | 0.0240219 | 3.522538 | 3.141262 | 2.645859 |
| 13 | -5.040341 | 3.778395 | 0.0240183 | 3.522519 | 3.141197 | 2.645729 |
| 14 | -5.040929 | 3.778653 | 0.0240164 | 3.522510 | 3.141163 | 2.645662 |
| 15 | -5.041235 | 3.778787 | 0.0240155 | 3.522506 | 3.141146 | 2.645627 |
| 16 | -5.041395 | 3.778857 | 0.0240150 | 3.522503 | 3.141138 | 2.645609 |
| 17 | -5.041478 | 3.778893 | 0.0240148 | 3.522502 | 3.141133 | 2.645600 |
| 18 | -5.041520 | 3.778912 | 0.0240146 | 3.522502 | 3.141131 | 2.645595 |
| 19 | -5.041543 | 3.778922 | 0.0240146 | 3.522501 | 3.141129 | 2.645593 |
| 20 | -5.041554 | 3.778927 | 0.0240145 | 3.522501 | 3.141129 | 2.645591 |
| 21 | -5.041560 | 3.778930 | 0.0240145 | 3.522501 | 3.141129 | 2.645591 |
| 22 | -5.041563 | 3.778931 | 0.0240145 | 3.522501 | 3.141128 | 2.645590 |
| 23 | -5.041565 | 3.778932 | 0.0240145 | 3.522501 | 3.141128 | 2.645590 |
| 24 | -5.041566 | 3.778932 | 0.0240145 | 3.522501 | 3.141128 | 2.645590 |
| NA | NA | NA | NA | NA | NA | NA |

1.6 Summary

Using Maximum Likelihood Mehtod, both Schmee & Hahn (1979), and Aitkin (1981) get a smaller $\hat{\beta}_0 = -6.019$, a larger $\hat{\beta}_1 = 4.311$, and larger estimate of the expected log time to failure times. I cannot reproduce these results. The estimates of removing 150c were not closer to each other too. In my attempts, Least Square Method and EM Method give similar results that ignoring the 150c data make $\hat{\beta}_1$ and $\hat{\mu}$ smaller.

| | Iteration | Intercept | Slope | Sigma | mu150 | mu170 | mu190 | mu220 |
|----------|-----------|-----------|----------|-----------|----------|----------|----------|----------|
| LS_full | 22 | -5.818118 | 4.204185 | 0.2043471 | 4.172998 | 3.876783 | 3.400929 | 2.879843 |
| EM_full | 57 | -5.457837 | 3.973333 | 0.0181290 | 3.944187 | 3.540115 | 3.139833 | 2.617184 |
| LS_no150 | 16 | -4.604230 | 3.636642 | 0.2410175 | NA | 3.886915 | 3.425672 | 2.932928 |
| EM_no150 | 24 | -5.041566 | 3.778932 | 0.0240145 | NA | 3.522501 | 3.141128 | 2.645590 |

2 Reference

Schmee, J., & Hahn, G. (1979). A Simple Method for Regression Analysis with Censored Data. Technometrics, 21(4), 417-432. doi:10.2307/1268280

Aitkin, M. (1981). A Note on the Regression Analysis of Censored Data. Technometrics, 23(2), 161-163. doi:10.2307/1268032