

Accelerated Failure Time

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1 Error - Normal Distribution

1.1 Uncensored Data

1.1.1 Loss Function

Loss $function_i = -\log-lik_i = -\log(f_{\hat{Y}_i}(\hat{y}_i))$
where,

$$\begin{aligned} z_i &= \frac{\ln y_i - \ln \hat{y}_i}{\sigma} \sim f \\ f(z) &= \frac{e^{-\frac{z^2}{2}}}{\sqrt{2\pi}} \\ f_{\hat{Y}}(\hat{y}) &= f_Z(z) \frac{\partial z}{\partial \hat{y}} \\ f_{\hat{Y}}(\hat{y}) &= \frac{\exp(\frac{(\ln(z) - \ln(\hat{y}))^2}{2\sigma^2})}{\hat{y}\sigma\sqrt{2\pi}} \\ Lossfunction_i &= -\log\left(\frac{\exp(\frac{(\ln(z_i) - \ln(\hat{y}_i))^2}{2\sigma^2})}{\hat{y}_i\sigma\sqrt{2\pi}}\right) \end{aligned} \tag{1}$$

1.1.2 Negative Gradient

$$\begin{aligned} -\frac{\partial Lossfunction_i}{\partial \hat{y}_i} &= \frac{\partial \log(f_{\hat{Y}_i}(\hat{y}_i))}{\partial \hat{y}_i} = \frac{1}{f_{\hat{Y}_i}(\hat{y}_i)} * \frac{\partial f_{\hat{Y}_i}(\hat{y}_i)}{\partial \hat{y}_i} \\ \frac{\partial f_{\hat{Y}}(\hat{y})}{\partial \hat{y}} &= \frac{\partial}{\partial \hat{y}} \left[f_Z(z) \frac{\partial z}{\partial \hat{y}} \right] \\ &= \frac{\partial f_Z(z)}{\partial \hat{y}} \frac{\partial z}{\partial \hat{y}} + f_Z(z) \frac{\partial^2 z}{\partial \hat{y}^2} \\ &= \frac{\partial f_Z(z)}{\partial z} \frac{\partial z^2}{\partial \hat{y}^2} + f_Z(z) \frac{\partial^2 z}{\partial \hat{y}^2} \\ &= \frac{-zf_Z(z)}{\sigma^2 \hat{y}^2} + \frac{f_Z(z)}{\sigma \hat{y}^2} \end{aligned} \tag{2}$$

$$\begin{aligned}\frac{\partial z}{\partial \hat{y}} &= \frac{-1}{\sigma \hat{y}} \\ \frac{\partial^2 z}{\partial \hat{y}^2} &= \frac{1}{\sigma \hat{y}^2}\end{aligned}\tag{3}$$

$$\frac{\partial f_Z(z)}{\partial z} = -zf_Z(z)$$

$$\begin{aligned}-\frac{\partial \text{Lossfunction}_i}{\partial \hat{y}_i} &= \frac{1}{f_{\hat{Y}_i}(\hat{y}_i)} * \frac{\partial f_{\hat{Y}_i}(\hat{y}_i)}{\partial \hat{y}_i} \\ &= \frac{1}{f_{\hat{Y}_i}(\hat{y}_i)} * \left\{ \frac{-z_i f_{Z_i}(z_i)}{\sigma^2 \hat{y}_i^2} + \frac{f_{Z_i}(z_i)}{\sigma \hat{y}_i^2} \right\} \\ &= \frac{f_{Z_i}(z_i)}{f_{\hat{Y}_i}(\hat{y}_i)} * \left\{ \frac{-z_i}{\sigma^2 \hat{y}_i^2} + \frac{1}{\sigma \hat{y}_i^2} \right\}\end{aligned}\tag{4}$$

$$\begin{aligned}f_{Z_i}(z_i) &= \frac{e^{-z_i^2/2}}{\sqrt{2\pi}} = \frac{e^{-\frac{(\ln y_i - \ln \hat{y}_i)^2}{2 * \sigma^2}}}{\sqrt{2\pi}} \\ f_{\hat{Y}_i}(\hat{y}_i) &= \frac{e^{-\frac{(\ln y_i - \ln \hat{y}_i)^2}{2 * \sigma^2}}}{\sqrt{2\pi} * \sigma * \hat{y}_i} \\ \frac{f_{Z_i}(z_i)}{f_{\hat{Y}_i}(\hat{y}_i)} &= \sigma * \hat{y}_i\end{aligned}\tag{5}$$

Coming back to equation 4

$$\begin{aligned}-\frac{\partial \text{Lossfunction}_i}{\partial \hat{y}_i} &= \frac{f_{Z_i}(z_i)}{f_{\hat{Y}_i}(\hat{y}_i)} * \left\{ \frac{-z_i}{\sigma^2 \hat{y}_i^2} + \frac{1}{\sigma \hat{y}_i^2} \right\} \\ &= \sigma * \hat{y}_i * \left\{ \frac{-z_i}{\sigma^2 \hat{y}_i^2} + \frac{1}{\sigma \hat{y}_i^2} \right\} \\ &= -\frac{\ln y_i - \ln \hat{y}_i}{\hat{y}_i \sigma^2} + \frac{1}{\hat{y}_i} \\ &= \frac{\sigma^2 - \ln \frac{y_i}{\hat{y}_i}}{\sigma^2 \hat{y}_i}\end{aligned}\tag{6}$$