Lista 1

Modelagem com Apoio Computacional

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Carregamento dos dados:

```
fatigue_df <- data.frame(
    work_MJ_m3 = c(

11.5,13.0,14.3,15.6,16.0,17.3,19.3,21.1,21.5,22.6,22.6,24.0,
24.0,24.6,25.2,25.5,26.3,27.9,28.3,28.4,28.6,30.9,31.9,34.5,
40.1,40.1,43.0,44.1,46.5,47.3,48.7,52.9,56.6,59.9,60.2,
60.3,60.5,62.1,62.8,66.5,67.0,67.1,67.9,68.8,75.4,100.5 ),
    life_cycles = c(
3280,5046,1563,4707,977,2834,2266,2208,1040,700,1583,482,
804,1093,1125,884,1300,852,580,1066,1114,386,745,736,
750,316,456,552,355,242,190,127,185,255,195,
283,212,327,373,125,187,135,245,137,200,190))</pre>
```

```
work_MJ_m3 life_cycles
1
        11.5
                     3280
2
        13.0
                     5046
3
        14.3
                     1563
4
        15.6
                     4707
5
        16.0
                      977
        17.3
                     2834
```

Função para ajuste do modelo de moda (log-BS):

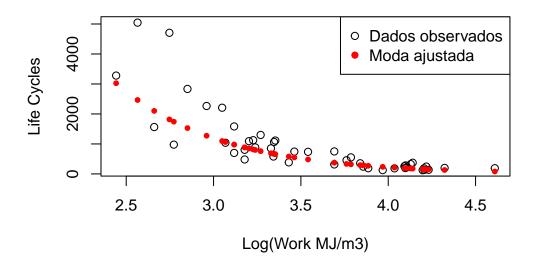
```
mle_mode_bs <- function(x, t) {</pre>
  x <- as.matrix(x)</pre>
  t <- as.matrix(t)
  fit_initial_log <- lm.fit(x, log(t))</pre>
  beta_initial_log_mode <- c(fit_initial_log$coef)</pre>
  k <- length(beta_initial_log_mode)</pre>
  n <- length(t)</pre>
  mu_initial_log <- x %*% beta_initial_log_mode</pre>
  alpha_initial_approx <- sqrt((4 / n) *</pre>
  sum((sinh((log(t) - mu_initial_log) / 2)) ^ 2))
  phi_initial <- alpha_initial_approx^2</pre>
  phi_initial \leftarrow \max(0.01, \min(0.99, \text{phi_initial}))
  thetaStar <- c(beta_initial_log_mode, phi_initial)</pre>
  loglik_mode <- function(par) {</pre>
    log_mode_Y <- x %*% par[1:k]</pre>
    phi_param <- par[k+1]</pre>
    if (phi_param <= 0 || phi_param >= 1) {
      return(NA)}
    alpha_orig <- sqrt(phi_param)</pre>
    beta_orig <- exp(log_mode_Y) / (1 - phi_param)</pre>
    terms <- log(t)
    l_i \leftarrow -\log(alpha_orig) - 0.5 * \log(2 * pi) - 0.5 * terms +
            log(sqrt(t / beta_orig) + sqrt(beta_orig / t)) -
            (1 / (2 * alpha_orig^2)) * (t / beta_orig + beta_orig / t - 2)
    if (any(!is.finite(l_i))) {
      return(.Machine$double.xmax)}
    return(-sum(l_i))}
  est <- optim(
    par = thetaStar,
    fn = loglik_mode,
    method = "BFGS",
```

```
hessian = TRUE,
  control = list(maxit = 2000, reltol = 1e-12))
if (est$conv != 0) {
  warning("FUNCTION DID NOT CONVERGE!")
coef <- (est$par)[1:k]</pre>
phi_est <- est$par[k + 1]</pre>
mode_hat_log <- x %*% coef</pre>
mode_hat <- exp(mode_hat_log)</pre>
SHess = solve(est$hessian)
SE = sqrt(diag(SHess))
tval = est$par / SE
matcoef = cbind(est$par, SE, tval, 2 * (1 - pnorm(abs(tval))))
AIC <- 2 * \text{ est}$value + 2 * (k + 1)
BIC \leftarrow 2 * est$value + (k + 1) * log(n)
result <- list(</pre>
  phiHat = phi_est,
 betaHat_log_mode = coef,
  modeHat = mode_hat,
  AIC = AIC,
  BIC = BIC,
  matcoef = matcoef
return(result)
```

Estimativas do modelo com base na moda:

```
SE tval
(Intercept) 12.095313 0.39169573 30.879358 0.00000e+00
log(fatigue_df$work_MJ_m3) -1.670763 0.10844480 -15.406574 0.00000e+00
0.168396 0.03510972 4.796278 1.61641e-06
```

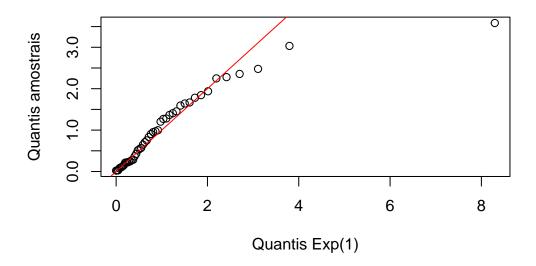
Dados observados e moda ajustada



Análise do ajuste do modelo com base na moda:

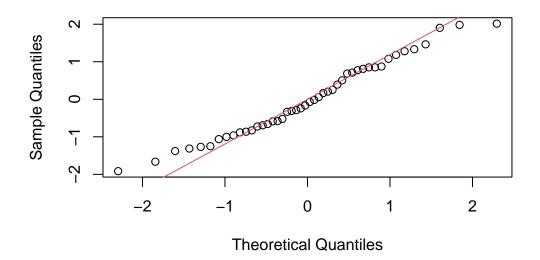
```
S_bs_mode <- function(y, mu, phi) {</pre>
  alpha <- sqrt(phi)</pre>
  beta <- mu / (1 - phi)
  xi <- (sqrt(y/beta) - sqrt(beta/y)) / alpha</pre>
  S <- 1 - pnorm(xi)
  return(S)
}
residuos_bs_mode <- function(y, mu_hat, phi_hat) {</pre>
  S <- S_bs_mode(y, mu_hat, phi_hat)</pre>
  r_{cox} \leftarrow -\log(S)
  r_quant <- qnorm(S)</pre>
  list(coxsnell = r_cox, quantile = r_quant)
res_mode <- residuos_bs_mode(</pre>
  y = fatigue_df$life_cycles,
  mu_hat = fit_mode_bs$modeHat,
  phi_hat = fit_mode_bs$phiHat
```

QQ-plot Resíduos



```
# QQ plot Quantilicos
qqnorm(res_mode$quantile); qqline(res_mode$quantile, col=2)
```

Normal Q-Q Plot



Ambos gráficos são bem similares aos gráficos para o modelo baseado na média.

Comparação com o modelo com base na média:

		se.coef	tval
(Intercept)	12.2797340	0.3893978	31.535187 0
<pre>log(fatigue_df\$work_MJ_m3)</pre>	-1.6707690	0.1084439	-15.406766 0
	0.4103574	0.0427819	9.591846 0