

Etas_approximations

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Temporal ETAS model

Here, we investigate various methodology to approximate a temporal ETAS model. A temporal ETAS model is a marked point process model, specifically an Hawkes process, with conditional intensity given by:

$$\lambda(t)|\mathcal{H}_t = \mu + K \sum_{i:t_i < t} \exp(\alpha(m_i - M_0)) \frac{1}{(t - t_i + c)^p}$$

where $\mathcal{H}_t = \{(t_i, m_i)\}$ is the history of the process. The model, as we present it, has 5 parameters μ, K, α, c, p which have to be non-negative, except for p which has to be greater than 1.

To be free from any constraint we are going to consider a different parametrization, specifically $\mu = \exp \theta_1$, $K = \exp \theta_2$, $\alpha = \exp \theta_3$, $c = \exp \theta_4$, $p - 1 = \exp \theta_5$. Now the parameters θ_i are free from any constraint. The conditional intensity that we are going to consider is

$$\lambda(t)|\mathcal{H}_t = \exp(\theta_1) + \exp(\theta_2) \sum_{i:t_i < t} \exp\left(\exp(\theta_3)(m_i - M_0)\right) \frac{1}{(t - t_i + \exp \theta_4)^{1+\exp \theta_5}}$$

Parametrized in this way, the conditional intensity is an increasing function of $\theta_1, \theta_2, \theta_3$, and a decreasing function of θ_4, θ_5 .

The expected number of points in (T_1, T_2) by the model is given by:

$$\begin{aligned} \Lambda(T_1, T_2) &= \int_{T_1}^{T_2} \lambda(t) dt = \int_{T_1}^{T_2} \left(\exp(\theta_1) + \exp(\theta_2) \sum_{i:t_i < t} \exp\left(\exp(\theta_3)(m_i - M_0)\right) \frac{1}{(t - t_i + \exp \theta_4)^{1+\exp \theta_5}} \right) dt \\ &= \exp(\theta_1)(T_2 - T_1) + \exp(\theta_2) \int_{T_1}^{T_2} \sum_{i:t_i \in \mathcal{H}_t} \exp\left(\exp(\theta_3)(m_i - M_0)\right) \frac{1}{(t - t_i + \exp \theta_4)^{1+\exp \theta_5}} \mathbb{I}(t_i < t) dt \\ &= \exp(\theta_1)(T_2 - T_1) + \exp(\theta_2) \left(\sum_{i:t_i < T_1} \exp\left(\exp(\theta_3)(m_i - M_0)\right) \int_{T_1}^{T_2} \frac{1}{(t - t_i + \exp \theta_4)^{1+\exp \theta_5}} \mathbb{I}(t_i < t) dt + \right. \\ &\quad \left. \sum_{i:t_i \geq T_1} \exp\left(\exp(\theta_3)(m_i - M_0)\right) \int_{T_1}^{T_2} \frac{1}{(t - t_i + \exp \theta_4)^{1+\exp \theta_5}} \mathbb{I}(t_i < t) dt \right) \end{aligned}$$

Where, assuming $T_1 > t_i$

$$\begin{aligned}
\int_{T_1}^{T_2} (t - t_i + \exp \theta_4)^{-1 - \exp \theta_5} dt &= - \frac{(t - t_i + \exp \theta_4)^{-\exp \theta_5}}{\exp \theta_5} \Big|_{T_1}^{T_2} \\
&= \frac{(T_1 - t_i + \exp \theta_4)^{-\exp \theta_5}}{\exp \theta_5} - \frac{(T_2 - t_i + \exp \theta_4)^{-\exp \theta_5}}{\exp \theta_5}
\end{aligned}$$

While

$$\int_{t_i}^{T_2} (t - t_i + \exp \theta_4)^{-1 - \exp \theta_5} dt = \frac{\exp(\theta_4)^{-\exp \theta_5}}{\exp \theta_5} - \frac{(T_2 - t_i + \exp \theta_4)^{-\exp \theta_5}}{\exp \theta_5}$$

Which leads to

$$\begin{aligned}
\Lambda(T_1, T_2) &= \int_{T_1}^{T_2} \lambda(t) dt = \\
&= \exp(\theta_1)(T_2 - T_1) + \exp(\theta_2) \left(\sum_{i: t_i < T_1} \exp \left(\exp(\theta_3)(m_i - M_0) \right) \left(\frac{(T_1 - t_i + \exp \theta_4)^{-\exp \theta_5}}{\exp \theta_5} - \right. \right. \\
&\quad \left. \frac{(T_2 - t_i + \exp \theta_4)^{-\exp \theta_5}}{\exp \theta_5} \right) + \sum_{i: t_i \geq T_1} \exp \left(\exp(\theta_3)(m_i - M_0) \right) \left(\frac{(\exp \theta_4)^{-\exp \theta_5}}{\exp \theta_5} - \right. \\
&\quad \left. \left. \frac{(T_2 - t_i + \exp \theta_4)^{-\exp \theta_5}}{\exp \theta_5} \right) \right)
\end{aligned}$$

This is the intensity and the expected number of points of the process without considering the marks. The effect of the mark is considered only inside the triggering function.

The expression of the number of points seen above is the most general case for which we are interested in the expected number of points in an interval which has observations inside it and before it. The first summation is the contribution to the expected number of points given by the *past* (observations s.t. $t_i < T_1$) while the second summation is the contribution given by the *present* (observations $t_i > T_1$). In practice, these cases rarely happens together. Indeed, if we are interested in the likelihood of the model then $T_1 < t_i$ and we have only the second summation. If we are interested in predicting the future given the past then $T_1 > t_i$ and we have only the first summation.

We have than if $T_1 > t_i$ for any $t_i \in \mathcal{H}_t$

$$\Lambda(T_1, T_2) = \exp(\theta_1)(T_2 - T_1) + \exp(\theta_2) \sum_{i: t_i \in \mathcal{H}_t} \exp \left(\exp(\theta_3)(m_i - M_0) \right) \left(\frac{(T_1 - t_i + \exp \theta_4)^{-\exp \theta_5}}{\exp \theta_5} - \frac{(T_2 - t_i + \exp \theta_4)^{-\exp \theta_5}}{\exp \theta_5} \right)$$

If $t_i \geq T_1$ for any $t_i \in \mathcal{H}_t$

$$\Lambda(T_1, T_2) = \exp(\theta_1)(T_2 - T_1) + \exp(\theta_2) \sum_{i: t_i \in \mathcal{H}_t} \exp\left(\exp(\theta_3)(m_i - M_0)\right) \left(\frac{(\exp \theta_4)^{-\exp \theta_5}}{\exp \theta_5} - \frac{(T_2 - t_i + \exp \theta_4)^{-\exp \theta_5}}{\exp \theta_5} \right)$$

From here we can see that, in the last case, the expected number of points is an increasing function of $\theta_1, \theta_2, \theta_3$ because $m_i - M_0 \geq 0$, and a decreasing function of θ_4, θ_5 .

Given a set of N observations $\mathcal{H}_t = \{(t_i, m_i), i = 1, \dots, N\}$ such that $t_i \in [T_1, T_2]$ for any $i = 1, \dots, N$ the likelihood of the model is given by:

$$\begin{aligned} \mathcal{L}(\theta) &= -\Lambda(T_1, T_2) + \sum_{i=1}^N \log \lambda(t_i) \\ &= -\left(\exp(\theta_1)(T_2 - T_1) + \exp(\theta_2) \sum_{i: t_i \in \mathcal{H}_t} \exp\left(\exp(\theta_3)(m_i - M_0)\right) \left(\frac{(\exp \theta_4)^{-\exp \theta_5}}{\exp \theta_5} - \frac{(T_2 - t_i + \exp \theta_4)^{-\exp \theta_5}}{\exp \theta_5} \right) \right) + \\ &\quad \sum_{i=1}^N \log \left(\exp(\theta_1) + \exp(\theta_2) \sum_{j: t_j < t_i} \exp\left(\exp(\theta_3)(m_j - M_0)\right) \frac{1}{(t_i - t_j + \exp \theta_4)^{1 + \exp \theta_5}} \right) \end{aligned}$$

```
source('ETAS_utils.R')

## Loading required package: viridisLite
## Loading required package: sp
## Loading required package: Matrix
## Loading required package: foreach
## Loading required package: parallel

## This is INLA_21.02.23 built 2021-03-15 10:11:24 UTC.
## - See www.r-inla.org/contact-us for how to get help.
## - To enable PARDISO sparse library; see inla.pardiso()
## - Save 273.9Mb of storage running 'inla.prune()'

##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##   filter, lag

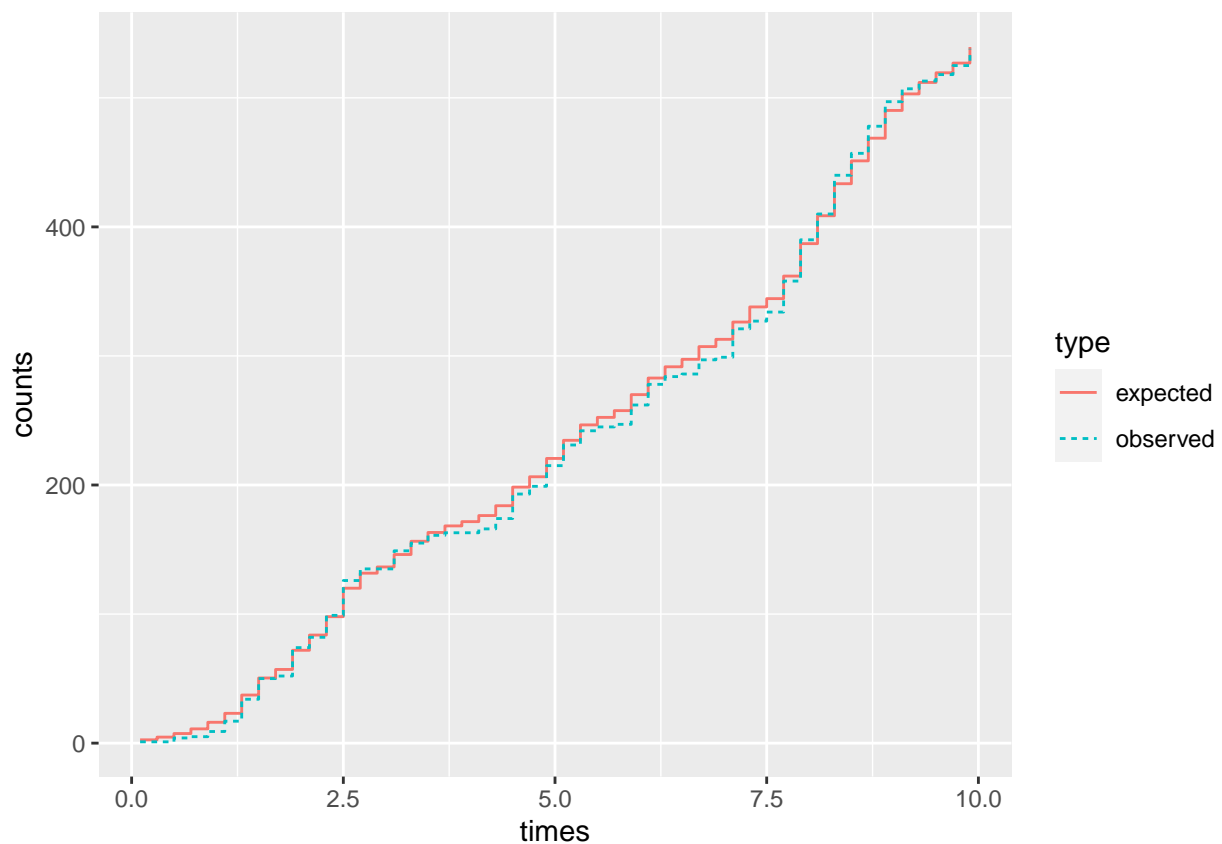
## The following objects are masked from 'package:base':
##
##   intersect, setdiff, setequal, union

##
## Attaching package: 'data.table'

## The following objects are masked from 'package:dplyr':
##
##   between, first, last
```

```
## The following object is masked from 'package:inlabru':
##
##   like
##
## Attaching package: 'metR'
##
## The following object is masked from 'package:INLA':
##
##   f
##
## Attaching package: 'matrixStats'
##
## The following object is masked from 'package:dplyr':
##
##   count
t.parms <- log(c(10, 0.8*(0.01^0.5)*0.5, 0.2, 0.01, 0.5))
Tlim = 10
# ss2 <- sample.ETAS.unnorm(t.parms, beta.par = 2.3, M0 = 2.5, Tlim)
# save(ss2, file = 'sample.etas.RData')

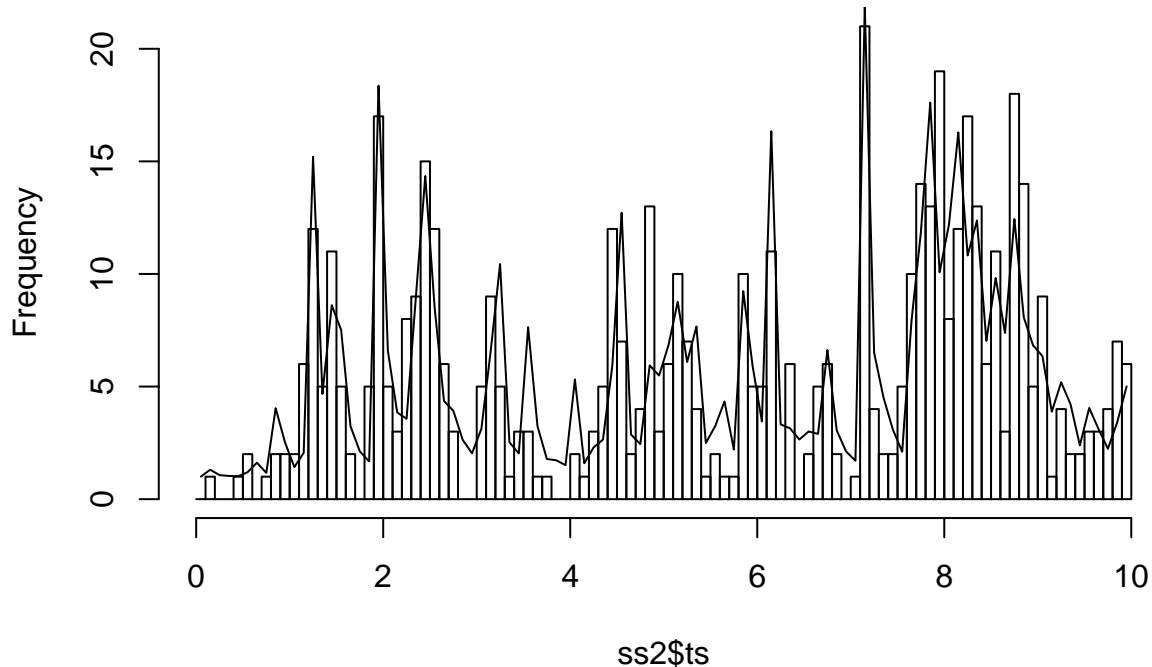
load('sample.etas.RData')
toplot.cumcounts(Tlim, t.parms, ss2, M0 = 2.5, by.s = 0.2)
```



```
t.breaks <- seq(0, Tlim, by = 0.1)
hh <- hist(ss2$ts, breaks = t.breaks, plot = FALSE)
ll <- log.lambda.ETAS(hh$mids, t.parms, ss2, M0 = 2.5)
```

```
plot(hh)
lines(hh$mids, exp(ll)*0.1)
```

Histogram of ss2\$ts



```
ML.optim <- optim(c(0,0,0,0,0), ETAS.log.lik.toptim, Ht = ss2, M0 = 2.5, Tlim = 10)
```

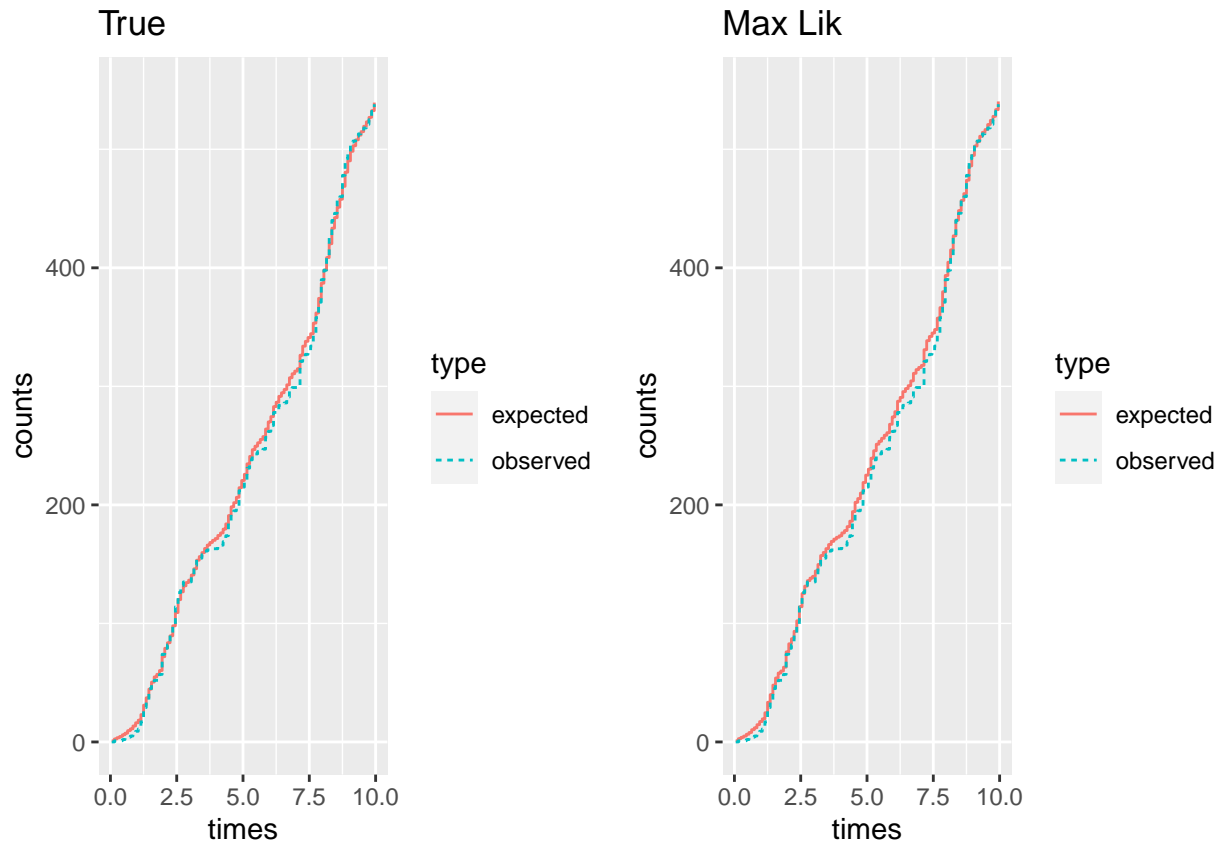
```
rbind(ML = exp(ML.optim$par), True = exp(t.parms))
```

```
##          [,1]      [,2]      [,3]      [,4]      [,5]
## ML  10.55479 0.01415566 8.781532e-06 0.0146675 0.9483153
## True 10.00000 0.04000000 2.000000e-01 0.0100000 0.5000000
```

```
pl.cs.ML <- toplot.cumcounts(10, ML.optim$par, ss2, 2.5, 0.1) + labs(title = 'Max Lik') +
  ylim(0,550)
```

```
pl.cs.true <- toplot.cumcounts(10, t.parms, ss2, 2.5, 0.1) + labs(title = 'True') +
  ylim(0,550)
```

```
multiplot(pl.cs.true, pl.cs.ML, cols = 2)
```



```
# univariate likelihood analysis
toplot.univ.comp <- function(par.values, par.idx, par.name,
                             theta.par, ML.est, Ht, M0, Tlim){

  theta.m.true <- cbind(rep(t.parms[1], length(par.values)),
                        rep(t.parms[2], length(par.values)),
                        rep(t.parms[3], length(par.values)),
                        rep(t.parms[4], length(par.values)),
                        rep(t.parms[5], length(par.values)))

  theta.m.ML <- cbind(rep(ML.est[1], length(par.values)),
                     rep(ML.est[2], length(par.values)),
                     rep(ML.est[3], length(par.values)),
                     rep(ML.est[4], length(par.values)),
                     rep(ML.est[5], length(par.values)))

  theta.m.true[,par.idx] <- par.values
  theta.m.ML[,par.idx] <- par.values

  LL.true <- sapply(1:nrow(theta.m.true), function(i)
    ETAS.log.lik(theta.m.true[i,], Ht, M0, Tlim))

  LL.ML <- sapply(1:nrow(theta.m.ML), function(i)
    ETAS.log.lik(theta.m.ML[i,], Ht, M0, Tlim))

  ll.lim <- range(c(LL.true, LL.ML))
}
```

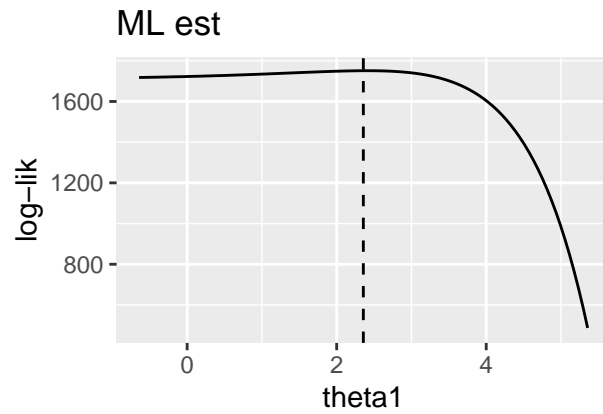
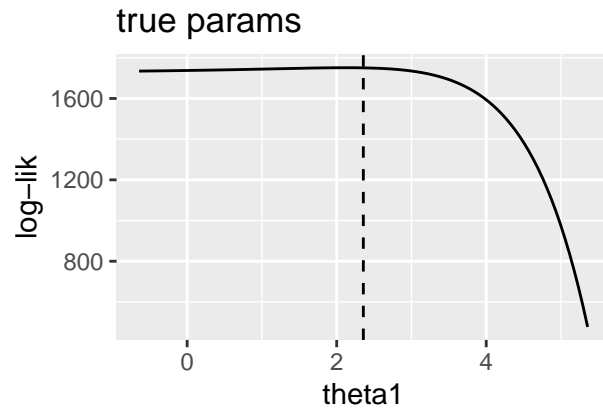
```

df <- rbind(data.frame(x = par.values,
                        y = LL.ML,
                        typ = 'ml'),
            data.frame(x = par.values,
                        y = LL.true,
                        typ = 'true'))
list(pl.true = ggplot(data.frame(x = par.values,
                                y = LL.true), aes(x = x, y = y)) +
      geom_line() +
      geom_vline(xintercept = ML.est[par.idx], linetype = 2) +
      labs(title = 'true params') +
      ylab('log-lik') +
      xlab(par.name) +
      ylim(ll.lim),
      pl.ML = ggplot(data.frame(x = par.values,
                                y = LL.ML), aes(x = x, y = y)) +
      geom_line() +
      geom_vline(xintercept = ML.est[par.idx], linetype = 2) +
      labs(title = 'ML est') +
      ylab('log-lik') +
      xlab(par.name) +
      ylim(ll.lim),
      df = df)
}

const <- 3
theta1.v <- seq(ML.optim$par[1] - const,
               ML.optim$par[1] + const, length.out = 100)
plot1.th1 <- toplot.univ.comp(theta1.v, 1, 'theta1', t.parms, ML.optim$par,
                             ss2, M0 = 2.5, Tlim = 10)

multiplot(plotlist = plot1.th1, cols = 2)

```



| ## | x | y | typ |
|-------|-------------|-----------|-----|
| ## 1 | -0.64341996 | 1717.7388 | ml |
| ## 2 | -0.58281390 | 1718.1271 | ml |
| ## 3 | -0.52220784 | 1718.5293 | ml |
| ## 4 | -0.46160178 | 1718.9460 | ml |
| ## 5 | -0.40099572 | 1719.3776 | ml |
| ## 6 | -0.34038966 | 1719.8248 | ml |
| ## 7 | -0.27978360 | 1720.2878 | ml |
| ## 8 | -0.21917753 | 1720.7672 | ml |
| ## 9 | -0.15857147 | 1721.2634 | ml |
| ## 10 | -0.09796541 | 1721.7769 | ml |
| ## 11 | -0.03735935 | 1722.3081 | ml |
| ## 12 | 0.02324671 | 1722.8575 | ml |
| ## 13 | 0.08385277 | 1723.4253 | ml |
| ## 14 | 0.14445883 | 1724.0120 | ml |
| ## 15 | 0.20506489 | 1724.6179 | ml |
| ## 16 | 0.26567095 | 1725.2432 | ml |
| ## 17 | 0.32627701 | 1725.8881 | ml |
| ## 18 | 0.38688307 | 1726.5529 | ml |
| ## 19 | 0.44748913 | 1727.2376 | ml |
| ## 20 | 0.50809519 | 1727.9423 | ml |
| ## 21 | 0.56870125 | 1728.6668 | ml |
| ## 22 | 0.62930731 | 1729.4110 | ml |
| ## 23 | 0.68991337 | 1730.1747 | ml |
| ## 24 | 0.75051943 | 1730.9575 | ml |
| ## 25 | 0.81112550 | 1731.7588 | ml |
| ## 26 | 0.87173156 | 1732.5780 | ml |

| | | | |
|-------|------------|-----------|----|
| ## 27 | 0.93233762 | 1733.4143 | ml |
| ## 28 | 0.99294368 | 1734.2666 | ml |
| ## 29 | 1.05354974 | 1735.1337 | ml |
| ## 30 | 1.11415580 | 1736.0143 | ml |
| ## 31 | 1.17476186 | 1736.9065 | ml |
| ## 32 | 1.23536792 | 1737.8084 | ml |
| ## 33 | 1.29597398 | 1738.7179 | ml |
| ## 34 | 1.35658004 | 1739.6323 | ml |
| ## 35 | 1.41718610 | 1740.5488 | ml |
| ## 36 | 1.47779216 | 1741.4639 | ml |
| ## 37 | 1.53839822 | 1742.3741 | ml |
| ## 38 | 1.59900428 | 1743.2752 | ml |
| ## 39 | 1.65961034 | 1744.1624 | ml |
| ## 40 | 1.72021640 | 1745.0306 | ml |
| ## 41 | 1.78082247 | 1745.8741 | ml |
| ## 42 | 1.84142853 | 1746.6865 | ml |
| ## 43 | 1.90203459 | 1747.4606 | ml |
| ## 44 | 1.96264065 | 1748.1887 | ml |
| ## 45 | 2.02324671 | 1748.8622 | ml |
| ## 46 | 2.08385277 | 1749.4717 | ml |
| ## 47 | 2.14445883 | 1750.0067 | ml |
| ## 48 | 2.20506489 | 1750.4560 | ml |
| ## 49 | 2.26567095 | 1750.8071 | ml |
| ## 50 | 2.32627701 | 1751.0465 | ml |
| ## 51 | 2.38688307 | 1751.1593 | ml |
| ## 52 | 2.44748913 | 1751.1294 | ml |
| ## 53 | 2.50809519 | 1750.9393 | ml |
| ## 54 | 2.56870125 | 1750.5699 | ml |
| ## 55 | 2.62930731 | 1750.0005 | ml |
| ## 56 | 2.68991337 | 1749.2086 | ml |
| ## 57 | 2.75051943 | 1748.1697 | ml |
| ## 58 | 2.81112550 | 1746.8577 | ml |
| ## 59 | 2.87173156 | 1745.2438 | ml |
| ## 60 | 2.93233762 | 1743.2973 | ml |
| ## 61 | 2.99294368 | 1740.9848 | ml |
| ## 62 | 3.05354974 | 1738.2703 | ml |
| ## 63 | 3.11415580 | 1735.1151 | ml |
| ## 64 | 3.17476186 | 1731.4773 | ml |
| ## 65 | 3.23536792 | 1727.3120 | ml |
| ## 66 | 3.29597398 | 1722.5707 | ml |
| ## 67 | 3.35658004 | 1717.2014 | ml |
| ## 68 | 3.41718610 | 1711.1479 | ml |
| ## 69 | 3.47779216 | 1704.3503 | ml |
| ## 70 | 3.53839822 | 1696.7440 | ml |
| ## 71 | 3.59900428 | 1688.2598 | ml |
| ## 72 | 3.65961034 | 1678.8234 | ml |
| ## 73 | 3.72021640 | 1668.3554 | ml |
| ## 74 | 3.78082247 | 1656.7706 | ml |
| ## 75 | 3.84142853 | 1643.9779 | ml |
| ## 76 | 3.90203459 | 1629.8798 | ml |
| ## 77 | 3.96264065 | 1614.3723 | ml |
| ## 78 | 4.02324671 | 1597.3438 | ml |
| ## 79 | 4.08385277 | 1578.6755 | ml |
| ## 80 | 4.14445883 | 1558.2404 | ml |

```

## 81 4.20506489 1535.9030 ml
## 82 4.26567095 1511.5189 ml
## 83 4.32627701 1484.9339 ml
## 84 4.38688307 1455.9839 ml
## 85 4.44748913 1424.4938 ml
## 86 4.50809519 1390.2774 ml
## 87 4.56870125 1353.1362 ml
## 88 4.62930731 1312.8592 ml
## 89 4.68991337 1269.2215 ml
## 90 4.75051943 1221.9842 ml
## 91 4.81112550 1170.8932 ml
## 92 4.87173156 1115.6781 ml
## 93 4.93233762 1056.0517 ml
## 94 4.99294368 991.7086 ml
## 95 5.05354974 922.3243 ml
## 96 5.11415580 847.5540 ml
## 97 5.17476186 767.0316 ml
## 98 5.23536792 680.3679 ml
## 99 5.29597398 587.1498 ml
## 100 5.35658004 486.9384 ml
## 101 -0.64341996 1734.4760 true
## 102 -0.58281390 1734.7197 true
## 103 -0.52220784 1734.9710 true
## 104 -0.46160178 1735.2299 true
## 105 -0.40099572 1735.4968 true
## 106 -0.34038966 1735.7719 true
## 107 -0.27978360 1736.0554 true
## 108 -0.21917753 1736.3475 true
## 109 -0.15857147 1736.6484 true
## 110 -0.09796541 1736.9583 true
## 111 -0.03735935 1737.2775 true
## 112 0.02324671 1737.6060 true
## 113 0.08385277 1737.9440 true
## 114 0.14445883 1738.2917 true
## 115 0.20506489 1738.6491 true
## 116 0.26567095 1739.0164 true
## 117 0.32627701 1739.3935 true
## 118 0.38688307 1739.7805 true
## 119 0.44748913 1740.1773 true
## 120 0.50809519 1740.5837 true
## 121 0.56870125 1740.9996 true
## 122 0.62930731 1741.4248 true
## 123 0.68991337 1741.8589 true
## 124 0.75051943 1742.3014 true
## 125 0.81112550 1742.7519 true
## 126 0.87173156 1743.2096 true
## 127 0.93233762 1743.6738 true
## 128 0.99294368 1744.1436 true
## 129 1.05354974 1744.6179 true
## 130 1.11415580 1745.0953 true
## 131 1.17476186 1745.5744 true
## 132 1.23536792 1746.0534 true
## 133 1.29597398 1746.5304 true
## 134 1.35658004 1747.0032 true

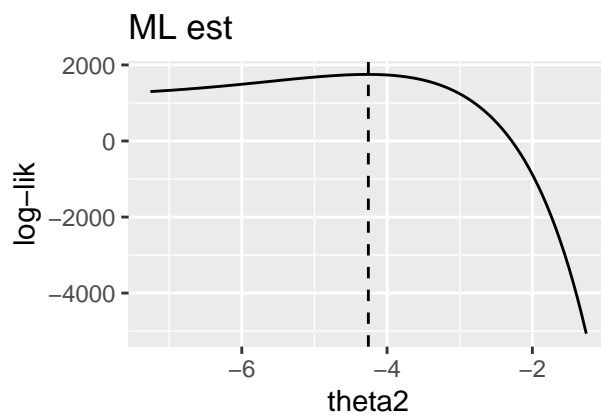
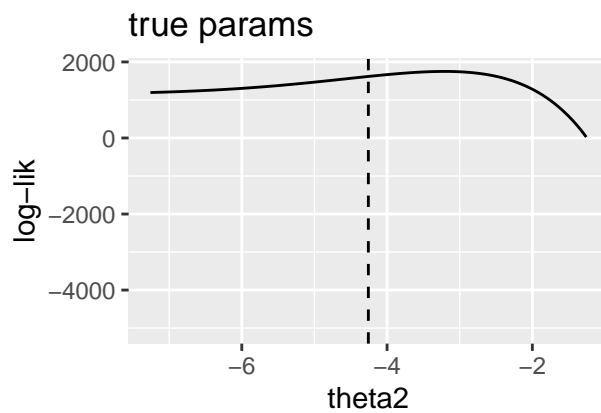
```

```
## 135 1.41718610 1747.4692 true
## 136 1.47779216 1747.9254 true
## 137 1.53839822 1748.3687 true
## 138 1.59900428 1748.7953 true
## 139 1.65961034 1749.2012 true
## 140 1.72021640 1749.5818 true
## 141 1.78082247 1749.9318 true
## 142 1.84142853 1750.2457 true
## 143 1.90203459 1750.5169 true
## 144 1.96264065 1750.7386 true
## 145 2.02324671 1750.9028 true
## 146 2.08385277 1751.0010 true
## 147 2.14445883 1751.0237 true
## 148 2.20506489 1750.9603 true
## 149 2.26567095 1750.7994 true
## 150 2.32627701 1750.5283 true
## 151 2.38688307 1750.1332 true
## 152 2.44748913 1749.5989 true
## 153 2.50809519 1748.9089 true
## 154 2.56870125 1748.0450 true
## 155 2.62930731 1746.9875 true
## 156 2.68991337 1745.7149 true
## 157 2.75051943 1744.2037 true
## 158 2.81112550 1742.4286 true
## 159 2.87173156 1740.3620 true
## 160 2.93233762 1737.9738 true
## 161 2.99294368 1735.2317 true
## 162 3.05354974 1732.1005 true
## 163 3.11415580 1728.5422 true
## 164 3.17476186 1724.5158 true
## 165 3.23536792 1719.9771 true
## 166 3.29597398 1714.8782 true
## 167 3.35658004 1709.1677 true
## 168 3.41718610 1702.7901 true
## 169 3.47779216 1695.6859 true
## 170 3.53839822 1687.7909 true
## 171 3.59900428 1679.0363 true
## 172 3.65961034 1669.3482 true
## 173 3.72021640 1658.6473 true
## 174 3.78082247 1646.8486 true
## 175 3.84142853 1633.8611 true
## 176 3.90203459 1619.5874 true
## 177 3.96264065 1603.9231 true
## 178 4.02324671 1586.7570 true
## 179 4.08385277 1567.9697 true
## 180 4.14445883 1547.4341 true
## 181 4.20506489 1525.0144 true
## 182 4.26567095 1500.5656 true
## 183 4.32627701 1473.9333 true
## 184 4.38688307 1444.9526 true
## 185 4.44748913 1413.4482 true
## 186 4.50809519 1379.2329 true
## 187 4.56870125 1342.1078 true
## 188 4.62930731 1301.8610 true
```

```
## 189 4.68991337 1258.2671 true
## 190 4.75051943 1211.0862 true
## 191 4.81112550 1160.0635 true
## 192 4.87173156 1104.9278 true
## 193 4.93233762 1045.3911 true
## 194 4.99294368 981.1471 true
## 195 5.05354974 911.8705 true
## 196 5.11415580 837.2157 true
## 197 5.17476186 756.8156 true
## 198 5.23536792 670.2804 true
## 199 5.29597398 577.1961 true
## 200 5.35658004 477.1230 true
```

```
# theta2
const <- 3
theta2.v <- seq(ML.optim$par[2] - const,
               ML.optim$par[2] + const, length.out = 100)
plotl.th2 <- topplot.univ.comp(theta2.v, 2, 'theta2', t.parms, ML.optim$par,
                              ss2, M0 = 2.5, Tlim = 10)

multiplot(plotlist = plotl.th2, cols = 2)
```



```
##      x      y typ
## 1 -7.257641 1300.54477 ml
## 2 -7.197035 1307.34157 ml
## 3 -7.136429 1314.39182 ml
## 4 -7.075823 1321.69796 ml
## 5 -7.015217 1329.26181 ml
```

| | | | |
|-------|-----------|------------|----|
| ## 6 | -6.954610 | 1337.08454 | ml |
| ## 7 | -6.894004 | 1345.16663 | ml |
| ## 8 | -6.833398 | 1353.50780 | ml |
| ## 9 | -6.772792 | 1362.10696 | ml |
| ## 10 | -6.712186 | 1370.96219 | ml |
| ## 11 | -6.651580 | 1380.07065 | ml |
| ## 12 | -6.590974 | 1389.42853 | ml |
| ## 13 | -6.530368 | 1399.03106 | ml |
| ## 14 | -6.469762 | 1408.87238 | ml |
| ## 15 | -6.409156 | 1418.94555 | ml |
| ## 16 | -6.348550 | 1429.24246 | ml |
| ## 17 | -6.287944 | 1439.75382 | ml |
| ## 18 | -6.227338 | 1450.46908 | ml |
| ## 19 | -6.166732 | 1461.37640 | ml |
| ## 20 | -6.106126 | 1472.46259 | ml |
| ## 21 | -6.045520 | 1483.71306 | ml |
| ## 22 | -5.984914 | 1495.11180 | ml |
| ## 23 | -5.924307 | 1506.64127 | ml |
| ## 24 | -5.863701 | 1518.28242 | ml |
| ## 25 | -5.803095 | 1530.01455 | ml |
| ## 26 | -5.742489 | 1541.81535 | ml |
| ## 27 | -5.681883 | 1553.66078 | ml |
| ## 28 | -5.621277 | 1565.52500 | ml |
| ## 29 | -5.560671 | 1577.38037 | ml |
| ## 30 | -5.500065 | 1589.19731 | ml |
| ## 31 | -5.439459 | 1600.94428 | ml |
| ## 32 | -5.378853 | 1612.58765 | ml |
| ## 33 | -5.318247 | 1624.09170 | ml |
| ## 34 | -5.257641 | 1635.41843 | ml |
| ## 35 | -5.197035 | 1646.52753 | ml |
| ## 36 | -5.136429 | 1657.37629 | ml |
| ## 37 | -5.075823 | 1667.91942 | ml |
| ## 38 | -5.015217 | 1678.10900 | ml |
| ## 39 | -4.954610 | 1687.89430 | ml |
| ## 40 | -4.894004 | 1697.22169 | ml |
| ## 41 | -4.833398 | 1706.03446 | ml |
| ## 42 | -4.772792 | 1714.27263 | ml |
| ## 43 | -4.712186 | 1721.87287 | ml |
| ## 44 | -4.651580 | 1728.76822 | ml |
| ## 45 | -4.590974 | 1734.88794 | ml |
| ## 46 | -4.530368 | 1740.15727 | ml |
| ## 47 | -4.469762 | 1744.49723 | ml |
| ## 48 | -4.409156 | 1747.82436 | ml |
| ## 49 | -4.348550 | 1750.05043 | ml |
| ## 50 | -4.287944 | 1751.08221 | ml |
| ## 51 | -4.227338 | 1750.82114 | ml |
| ## 52 | -4.166732 | 1749.16298 | ml |
| ## 53 | -4.106126 | 1745.99754 | ml |
| ## 54 | -4.045520 | 1741.20822 | ml |
| ## 55 | -3.984914 | 1734.67171 | ml |
| ## 56 | -3.924307 | 1726.25750 | ml |
| ## 57 | -3.863701 | 1715.82748 | ml |
| ## 58 | -3.803095 | 1703.23544 | ml |
| ## 59 | -3.742489 | 1688.32657 | ml |

| | | | |
|--------|-----------|-------------|------|
| ## 60 | -3.681883 | 1670.93694 | ml |
| ## 61 | -3.621277 | 1650.89290 | ml |
| ## 62 | -3.560671 | 1628.01051 | ml |
| ## 63 | -3.500065 | 1602.09484 | ml |
| ## 64 | -3.439459 | 1572.93931 | ml |
| ## 65 | -3.378853 | 1540.32497 | ml |
| ## 66 | -3.318247 | 1504.01969 | ml |
| ## 67 | -3.257641 | 1463.77734 | ml |
| ## 68 | -3.197035 | 1419.33694 | ml |
| ## 69 | -3.136429 | 1370.42168 | ml |
| ## 70 | -3.075823 | 1316.73792 | ml |
| ## 71 | -3.015217 | 1257.97418 | ml |
| ## 72 | -2.954610 | 1193.79998 | ml |
| ## 73 | -2.894004 | 1123.86465 | ml |
| ## 74 | -2.833398 | 1047.79604 | ml |
| ## 75 | -2.772792 | 965.19922 | ml |
| ## 76 | -2.712186 | 875.65499 | ml |
| ## 77 | -2.651580 | 778.71838 | ml |
| ## 78 | -2.590974 | 673.91704 | ml |
| ## 79 | -2.530368 | 560.74951 | ml |
| ## 80 | -2.469762 | 438.68336 | ml |
| ## 81 | -2.409156 | 307.15329 | ml |
| ## 82 | -2.348550 | 165.55906 | ml |
| ## 83 | -2.287944 | 13.26327 | ml |
| ## 84 | -2.227338 | -150.41097 | ml |
| ## 85 | -2.166732 | -326.18248 | ml |
| ## 86 | -2.106126 | -514.81469 | ml |
| ## 87 | -2.045520 | -717.11839 | ml |
| ## 88 | -1.984914 | -933.95475 | ml |
| ## 89 | -1.924307 | -1166.23841 | ml |
| ## 90 | -1.863701 | -1414.94093 | ml |
| ## 91 | -1.803095 | -1681.09424 | ml |
| ## 92 | -1.742489 | -1965.79450 | ml |
| ## 93 | -1.681883 | -2270.20612 | ml |
| ## 94 | -1.621277 | -2595.56599 | ml |
| ## 95 | -1.560671 | -2943.18806 | ml |
| ## 96 | -1.500065 | -3314.46812 | ml |
| ## 97 | -1.439459 | -3710.88898 | ml |
| ## 98 | -1.378853 | -4134.02587 | ml |
| ## 99 | -1.318247 | -4585.55224 | ml |
| ## 100 | -1.257641 | -5067.24588 | ml |
| ## 101 | -7.257641 | 1195.78391 | true |
| ## 102 | -7.197035 | 1199.01927 | true |
| ## 103 | -7.136429 | 1202.42024 | true |
| ## 104 | -7.075823 | 1205.99335 | true |
| ## 105 | -7.015217 | 1209.74518 | true |
| ## 106 | -6.954610 | 1213.68238 | true |
| ## 107 | -6.894004 | 1217.81158 | true |
| ## 108 | -6.833398 | 1222.13941 | true |
| ## 109 | -6.772792 | 1226.67245 | true |
| ## 110 | -6.712186 | 1231.41720 | true |
| ## 111 | -6.651580 | 1236.38007 | true |
| ## 112 | -6.590974 | 1241.56732 | true |
| ## 113 | -6.530368 | 1246.98500 | true |

```

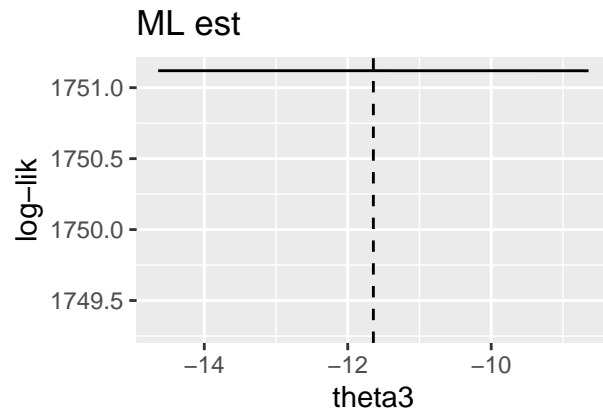
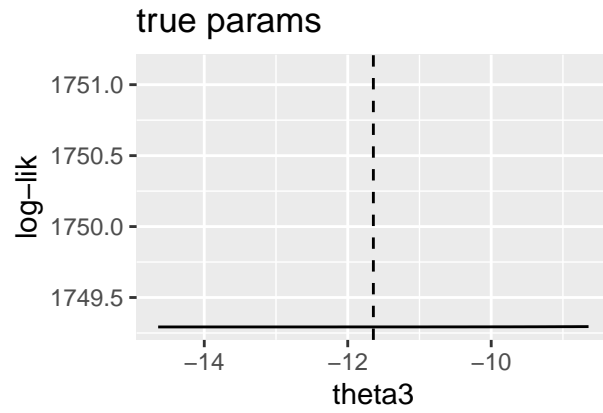
## 114 -6.469762 1252.63898 true
## 115 -6.409156 1258.53484 true
## 116 -6.348550 1264.67785 true
## 117 -6.287944 1271.07294 true
## 118 -6.227338 1277.72462 true
## 119 -6.166732 1284.63696 true
## 120 -6.106126 1291.81352 true
## 121 -6.045520 1299.25732 true
## 122 -5.984914 1306.97075 true
## 123 -5.924307 1314.95557 true
## 124 -5.863701 1323.21279 true
## 125 -5.803095 1331.74269 true
## 126 -5.742489 1340.54468 true
## 127 -5.681883 1349.61735 true
## 128 -5.621277 1358.95830 true
## 129 -5.560671 1368.56419 true
## 130 -5.500065 1378.43062 true
## 131 -5.439459 1388.55209 true
## 132 -5.378853 1398.92198 true
## 133 -5.318247 1409.53244 true
## 134 -5.257641 1420.37440 true
## 135 -5.197035 1431.43748 true
## 136 -5.136429 1442.70993 true
## 137 -5.075823 1454.17863 true
## 138 -5.015217 1465.82897 true
## 139 -4.954610 1477.64487 true
## 140 -4.894004 1489.60868 true
## 141 -4.833398 1501.70112 true
## 142 -4.772792 1513.90129 true
## 143 -4.712186 1526.18652 true
## 144 -4.651580 1538.53241 true
## 145 -4.590974 1550.91269 true
## 146 -4.530368 1563.29921 true
## 147 -4.469762 1575.66184 true
## 148 -4.409156 1587.96842 true
## 149 -4.348550 1600.18468 true
## 150 -4.287944 1612.27415 true
## 151 -4.227338 1624.19807 true
## 152 -4.166732 1635.91534 true
## 153 -4.106126 1647.38235 true
## 154 -4.045520 1658.55293 true
## 155 -3.984914 1669.37822 true
## 156 -3.924307 1679.80651 true
## 157 -3.863701 1689.78318 true
## 158 -3.803095 1699.25045 true
## 159 -3.742489 1708.14734 true
## 160 -3.681883 1716.40939 true
## 161 -3.621277 1723.96857 true
## 162 -3.560671 1730.75303 true
## 163 -3.500065 1736.68689 true
## 164 -3.439459 1741.69006 true
## 165 -3.378853 1745.67793 true
## 166 -3.318247 1748.56117 true
## 167 -3.257641 1750.24542 true

```

```
## 168 -3.197035 1750.63100 true
## 169 -3.136429 1749.61260 true
## 170 -3.075823 1747.07891 true
## 171 -3.015217 1742.91228 true
## 172 -2.954610 1736.98833 true
## 173 -2.894004 1729.17553 true
## 174 -2.833398 1719.33476 true
## 175 -2.772792 1707.31881 true
## 176 -2.712186 1692.97192 true
## 177 -2.651580 1676.12921 true
## 178 -2.590974 1656.61614 true
## 179 -2.530368 1634.24784 true
## 180 -2.469762 1608.82855 true
## 181 -2.409156 1580.15083 true
## 182 -2.348550 1547.99492 true
## 183 -2.287944 1512.12788 true
## 184 -2.227338 1472.30282 true
## 185 -2.166732 1428.25797 true
## 186 -2.106126 1379.71578 true
## 187 -2.045520 1326.38188 true
## 188 -1.984914 1267.94405 true
## 189 -1.924307 1204.07107 true
## 190 -1.863701 1134.41154 true
## 191 -1.803095 1058.59260 true
## 192 -1.742489 976.21854 true
## 193 -1.681883 886.86943 true
## 194 -1.621277 790.09951 true
## 195 -1.560671 685.43564 true
## 196 -1.500065 572.37550 true
## 197 -1.439459 450.38583 true
## 198 -1.378853 318.90040 true
## 199 -1.318247 177.31802 true
## 200 -1.257641 25.00027 true
```

```
# theta3
const <- 3
theta3.v <- seq(ML.optim$par[3] - const,
               ML.optim$par[3] + const, length.out = 100)
plotl.th3 <- topplot.univ.comp(theta3.v, 3, 'theta3', t.parms, ML.optim$par,
                              ss2, M0 = 2.5, Tlim = 10)

multiplot(plotlist = plotl.th3, cols = 2)
```

| ## | x | y | typ |
|-------|------------|----------|-----|
| ## 1 | -14.642860 | 1751.120 | ml |
| ## 2 | -14.582254 | 1751.120 | ml |
| ## 3 | -14.521648 | 1751.120 | ml |
| ## 4 | -14.461041 | 1751.120 | ml |
| ## 5 | -14.400435 | 1751.120 | ml |
| ## 6 | -14.339829 | 1751.120 | ml |
| ## 7 | -14.279223 | 1751.120 | ml |
| ## 8 | -14.218617 | 1751.120 | ml |
| ## 9 | -14.158011 | 1751.120 | ml |
| ## 10 | -14.097405 | 1751.120 | ml |
| ## 11 | -14.036799 | 1751.120 | ml |
| ## 12 | -13.976193 | 1751.120 | ml |
| ## 13 | -13.915587 | 1751.120 | ml |
| ## 14 | -13.854981 | 1751.120 | ml |
| ## 15 | -13.794375 | 1751.120 | ml |
| ## 16 | -13.733769 | 1751.120 | ml |
| ## 17 | -13.673163 | 1751.120 | ml |
| ## 18 | -13.612557 | 1751.120 | ml |
| ## 19 | -13.551951 | 1751.120 | ml |
| ## 20 | -13.491344 | 1751.120 | ml |
| ## 21 | -13.430738 | 1751.120 | ml |
| ## 22 | -13.370132 | 1751.120 | ml |
| ## 23 | -13.309526 | 1751.120 | ml |
| ## 24 | -13.248920 | 1751.120 | ml |
| ## 25 | -13.188314 | 1751.120 | ml |
| ## 26 | -13.127708 | 1751.120 | ml |

| | | | |
|-------|------------|----------|----|
| ## 27 | -13.067102 | 1751.120 | ml |
| ## 28 | -13.006496 | 1751.120 | ml |
| ## 29 | -12.945890 | 1751.120 | ml |
| ## 30 | -12.885284 | 1751.120 | ml |
| ## 31 | -12.824678 | 1751.120 | ml |
| ## 32 | -12.764072 | 1751.120 | ml |
| ## 33 | -12.703466 | 1751.120 | ml |
| ## 34 | -12.642860 | 1751.120 | ml |
| ## 35 | -12.582254 | 1751.120 | ml |
| ## 36 | -12.521648 | 1751.120 | ml |
| ## 37 | -12.461041 | 1751.120 | ml |
| ## 38 | -12.400435 | 1751.120 | ml |
| ## 39 | -12.339829 | 1751.120 | ml |
| ## 40 | -12.279223 | 1751.120 | ml |
| ## 41 | -12.218617 | 1751.120 | ml |
| ## 42 | -12.158011 | 1751.120 | ml |
| ## 43 | -12.097405 | 1751.120 | ml |
| ## 44 | -12.036799 | 1751.120 | ml |
| ## 45 | -11.976193 | 1751.120 | ml |
| ## 46 | -11.915587 | 1751.120 | ml |
| ## 47 | -11.854981 | 1751.120 | ml |
| ## 48 | -11.794375 | 1751.120 | ml |
| ## 49 | -11.733769 | 1751.120 | ml |
| ## 50 | -11.673163 | 1751.120 | ml |
| ## 51 | -11.612557 | 1751.120 | ml |
| ## 52 | -11.551951 | 1751.120 | ml |
| ## 53 | -11.491344 | 1751.120 | ml |
| ## 54 | -11.430738 | 1751.120 | ml |
| ## 55 | -11.370132 | 1751.120 | ml |
| ## 56 | -11.309526 | 1751.120 | ml |
| ## 57 | -11.248920 | 1751.120 | ml |
| ## 58 | -11.188314 | 1751.120 | ml |
| ## 59 | -11.127708 | 1751.120 | ml |
| ## 60 | -11.067102 | 1751.120 | ml |
| ## 61 | -11.006496 | 1751.120 | ml |
| ## 62 | -10.945890 | 1751.120 | ml |
| ## 63 | -10.885284 | 1751.120 | ml |
| ## 64 | -10.824678 | 1751.120 | ml |
| ## 65 | -10.764072 | 1751.120 | ml |
| ## 66 | -10.703466 | 1751.120 | ml |
| ## 67 | -10.642860 | 1751.120 | ml |
| ## 68 | -10.582254 | 1751.120 | ml |
| ## 69 | -10.521648 | 1751.120 | ml |
| ## 70 | -10.461041 | 1751.120 | ml |
| ## 71 | -10.400435 | 1751.120 | ml |
| ## 72 | -10.339829 | 1751.120 | ml |
| ## 73 | -10.279223 | 1751.120 | ml |
| ## 74 | -10.218617 | 1751.120 | ml |
| ## 75 | -10.158011 | 1751.120 | ml |
| ## 76 | -10.097405 | 1751.120 | ml |
| ## 77 | -10.036799 | 1751.120 | ml |
| ## 78 | -9.976193 | 1751.120 | ml |
| ## 79 | -9.915587 | 1751.120 | ml |
| ## 80 | -9.854981 | 1751.120 | ml |

```

## 81  -9.794375 1751.120  ml
## 82  -9.733769 1751.120  ml
## 83  -9.673163 1751.120  ml
## 84  -9.612557 1751.120  ml
## 85  -9.551951 1751.120  ml
## 86  -9.491344 1751.119  ml
## 87  -9.430738 1751.119  ml
## 88  -9.370132 1751.119  ml
## 89  -9.309526 1751.119  ml
## 90  -9.248920 1751.119  ml
## 91  -9.188314 1751.119  ml
## 92  -9.127708 1751.119  ml
## 93  -9.067102 1751.119  ml
## 94  -9.006496 1751.119  ml
## 95  -8.945890 1751.119  ml
## 96  -8.885284 1751.119  ml
## 97  -8.824678 1751.119  ml
## 98  -8.764072 1751.119  ml
## 99  -8.703466 1751.119  ml
## 100 -8.642860 1751.119  ml
## 101 -14.642860 1749.293 true
## 102 -14.582254 1749.293 true
## 103 -14.521648 1749.293 true
## 104 -14.461041 1749.293 true
## 105 -14.400435 1749.293 true
## 106 -14.339829 1749.293 true
## 107 -14.279223 1749.293 true
## 108 -14.218617 1749.293 true
## 109 -14.158011 1749.293 true
## 110 -14.097405 1749.293 true
## 111 -14.036799 1749.293 true
## 112 -13.976193 1749.293 true
## 113 -13.915587 1749.293 true
## 114 -13.854981 1749.293 true
## 115 -13.794375 1749.293 true
## 116 -13.733769 1749.293 true
## 117 -13.673163 1749.293 true
## 118 -13.612557 1749.293 true
## 119 -13.551951 1749.293 true
## 120 -13.491344 1749.293 true
## 121 -13.430738 1749.293 true
## 122 -13.370132 1749.293 true
## 123 -13.309526 1749.293 true
## 124 -13.248920 1749.293 true
## 125 -13.188314 1749.293 true
## 126 -13.127708 1749.293 true
## 127 -13.067102 1749.293 true
## 128 -13.006496 1749.293 true
## 129 -12.945890 1749.293 true
## 130 -12.885284 1749.293 true
## 131 -12.824678 1749.293 true
## 132 -12.764072 1749.293 true
## 133 -12.703466 1749.293 true
## 134 -12.642860 1749.293 true

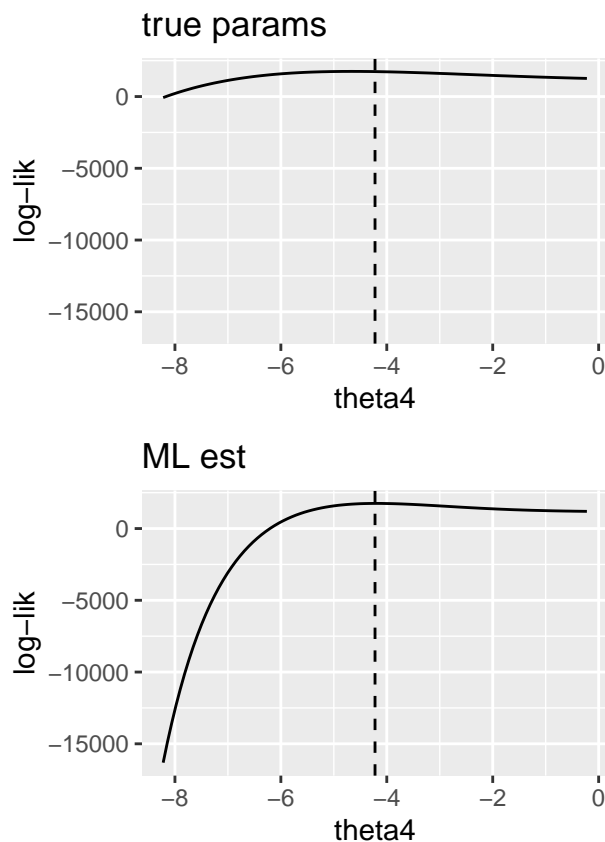
```

```
## 135 -12.582254 1749.293 true
## 136 -12.521648 1749.293 true
## 137 -12.461041 1749.293 true
## 138 -12.400435 1749.293 true
## 139 -12.339829 1749.293 true
## 140 -12.279223 1749.293 true
## 141 -12.218617 1749.293 true
## 142 -12.158011 1749.293 true
## 143 -12.097405 1749.293 true
## 144 -12.036799 1749.293 true
## 145 -11.976193 1749.293 true
## 146 -11.915587 1749.293 true
## 147 -11.854981 1749.293 true
## 148 -11.794375 1749.293 true
## 149 -11.733769 1749.293 true
## 150 -11.673163 1749.293 true
## 151 -11.612557 1749.293 true
## 152 -11.551951 1749.293 true
## 153 -11.491344 1749.293 true
## 154 -11.430738 1749.293 true
## 155 -11.370132 1749.293 true
## 156 -11.309526 1749.293 true
## 157 -11.248920 1749.293 true
## 158 -11.188314 1749.293 true
## 159 -11.127708 1749.293 true
## 160 -11.067102 1749.293 true
## 161 -11.006496 1749.293 true
## 162 -10.945890 1749.293 true
## 163 -10.885284 1749.293 true
## 164 -10.824678 1749.293 true
## 165 -10.764072 1749.293 true
## 166 -10.703466 1749.293 true
## 167 -10.642860 1749.293 true
## 168 -10.582254 1749.293 true
## 169 -10.521648 1749.293 true
## 170 -10.461041 1749.293 true
## 171 -10.400435 1749.293 true
## 172 -10.339829 1749.293 true
## 173 -10.279223 1749.293 true
## 174 -10.218617 1749.293 true
## 175 -10.158011 1749.293 true
## 176 -10.097405 1749.293 true
## 177 -10.036799 1749.293 true
## 178 -9.976193 1749.293 true
## 179 -9.915587 1749.293 true
## 180 -9.854981 1749.293 true
## 181 -9.794375 1749.293 true
## 182 -9.733769 1749.293 true
## 183 -9.673163 1749.293 true
## 184 -9.612557 1749.294 true
## 185 -9.551951 1749.294 true
## 186 -9.491344 1749.294 true
## 187 -9.430738 1749.294 true
## 188 -9.370132 1749.294 true
```

```
## 189 -9.309526 1749.294 true
## 190 -9.248920 1749.294 true
## 191 -9.188314 1749.294 true
## 192 -9.127708 1749.294 true
## 193 -9.067102 1749.294 true
## 194 -9.006496 1749.294 true
## 195 -8.945890 1749.294 true
## 196 -8.885284 1749.295 true
## 197 -8.824678 1749.295 true
## 198 -8.764072 1749.295 true
## 199 -8.703466 1749.295 true
## 200 -8.642860 1749.295 true
```

```
# theta4
const <- 4
theta4.v <- seq(ML.optim$par[4] - const,
               ML.optim$par[4] + const, length.out = 100)
plotl.th4 <- topplot.univ.comp(theta4.v, 4, 'theta4', t.parms, ML.optim$par,
                              ss2, M0 = 2.5, Tlim = 10)

multiplot(plotlist = plotl.th4, cols = 2)
```



| ## | x | y | typ |
|------|------------|--------------|-----|
| ## 1 | -8.2221213 | -16314.17423 | ml |
| ## 2 | -8.1413132 | -14879.93686 | ml |
| ## 3 | -8.0605052 | -13552.45160 | ml |
| ## 4 | -7.9796971 | -12323.88830 | ml |
| ## 5 | -7.8988890 | -11186.99572 | ml |

| | | | |
|-------|------------|--------------|----|
| ## 6 | -7.8180809 | -10135.05884 | ml |
| ## 7 | -7.7372728 | -9161.85924 | ml |
| ## 8 | -7.6564648 | -8261.63841 | ml |
| ## 9 | -7.5756567 | -7429.06377 | ml |
| ## 10 | -7.4948486 | -6659.19718 | ml |
| ## 11 | -7.4140405 | -5947.46577 | ml |
| ## 12 | -7.3332324 | -5289.63493 | ml |
| ## 13 | -7.2524244 | -4681.78321 | ml |
| ## 14 | -7.1716163 | -4120.27916 | ml |
| ## 15 | -7.0908082 | -3601.75982 | ml |
| ## 16 | -7.0100001 | -3123.11079 | ml |
| ## 17 | -6.9291920 | -2681.44772 | ml |
| ## 18 | -6.8483839 | -2274.09927 | ml |
| ## 19 | -6.7675759 | -1898.59121 | ml |
| ## 20 | -6.6867678 | -1552.63170 | ml |
| ## 21 | -6.6059597 | -1234.09773 | ml |
| ## 22 | -6.5251516 | -941.02242 | ml |
| ## 23 | -6.4443435 | -671.58339 | ml |
| ## 24 | -6.3635355 | -424.09186 | ml |
| ## 25 | -6.2827274 | -196.98264 | ml |
| ## 26 | -6.2019193 | 11.19522 | ml |
| ## 27 | -6.1211112 | 201.78702 | ml |
| ## 28 | -6.0403031 | 376.04046 | ml |
| ## 29 | -5.9594951 | 535.11299 | ml |
| ## 30 | -5.8786870 | 680.07873 | ml |
| ## 31 | -5.7978789 | 811.93482 | ml |
| ## 32 | -5.7170708 | 931.60728 | ml |
| ## 33 | -5.6362627 | 1039.95652 | ml |
| ## 34 | -5.5554547 | 1137.78236 | ml |
| ## 35 | -5.4746466 | 1225.82873 | ml |
| ## 36 | -5.3938385 | 1304.78799 | ml |
| ## 37 | -5.3130304 | 1375.30494 | ml |
| ## 38 | -5.2322223 | 1437.98055 | ml |
| ## 39 | -5.1514142 | 1493.37536 | ml |
| ## 40 | -5.0706062 | 1542.01267 | ml |
| ## 41 | -4.9897981 | 1584.38146 | ml |
| ## 42 | -4.9089900 | 1620.93910 | ml |
| ## 43 | -4.8281819 | 1652.11381 | ml |
| ## 44 | -4.7473738 | 1678.30695 | ml |
| ## 45 | -4.6665658 | 1699.89513 | ml |
| ## 46 | -4.5857577 | 1717.23215 | ml |
| ## 47 | -4.5049496 | 1730.65068 | ml |
| ## 48 | -4.4241415 | 1740.46391 | ml |
| ## 49 | -4.3433334 | 1746.96698 | ml |
| ## 50 | -4.2625254 | 1750.43825 | ml |
| ## 51 | -4.1817173 | 1751.14050 | ml |
| ## 52 | -4.1009092 | 1749.32196 | ml |
| ## 53 | -4.0201011 | 1745.21722 | ml |
| ## 54 | -3.9392930 | 1739.04807 | ml |
| ## 55 | -3.8584850 | 1731.02427 | ml |
| ## 56 | -3.7776769 | 1721.34412 | ml |
| ## 57 | -3.6968688 | 1710.19511 | ml |
| ## 58 | -3.6160607 | 1697.75441 | ml |
| ## 59 | -3.5352526 | 1684.18934 | ml |

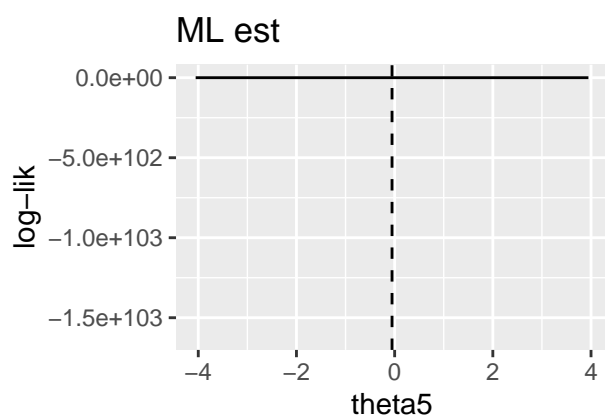
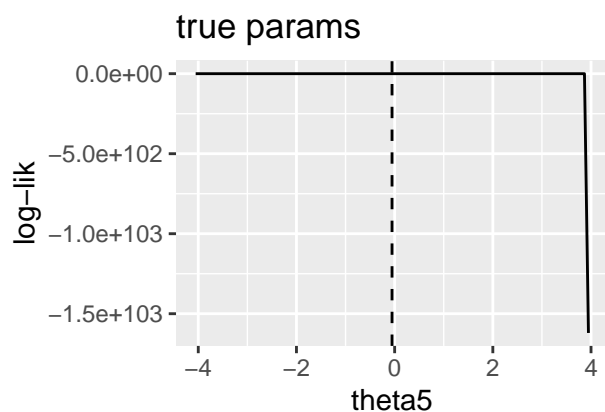
| | | | |
|--------|------------|------------|------|
| ## 60 | -3.4544446 | 1669.65778 | ml |
| ## 61 | -3.3736365 | 1654.30856 | ml |
| ## 62 | -3.2928284 | 1638.28179 | ml |
| ## 63 | -3.2120203 | 1621.70916 | ml |
| ## 64 | -3.1312122 | 1604.71424 | ml |
| ## 65 | -3.0504041 | 1587.41269 | ml |
| ## 66 | -2.9695961 | 1569.91245 | ml |
| ## 67 | -2.8887880 | 1552.31398 | ml |
| ## 68 | -2.8079799 | 1534.71033 | ml |
| ## 69 | -2.7271718 | 1517.18731 | ml |
| ## 70 | -2.6463637 | 1499.82355 | ml |
| ## 71 | -2.5655557 | 1482.69061 | ml |
| ## 72 | -2.4847476 | 1465.85308 | ml |
| ## 73 | -2.4039395 | 1449.36860 | ml |
| ## 74 | -2.3231314 | 1433.28804 | ml |
| ## 75 | -2.2423233 | 1417.65556 | ml |
| ## 76 | -2.1615153 | 1402.50876 | ml |
| ## 77 | -2.0807072 | 1387.87893 | ml |
| ## 78 | -1.9998991 | 1373.79123 | ml |
| ## 79 | -1.9190910 | 1360.26497 | ml |
| ## 80 | -1.8382829 | 1347.31395 | ml |
| ## 81 | -1.7574749 | 1334.94683 | ml |
| ## 82 | -1.6766668 | 1323.16746 | ml |
| ## 83 | -1.5958587 | 1311.97540 | ml |
| ## 84 | -1.5150506 | 1301.36626 | ml |
| ## 85 | -1.4342425 | 1291.33221 | ml |
| ## 86 | -1.3534345 | 1281.86241 | ml |
| ## 87 | -1.2726264 | 1272.94344 | ml |
| ## 88 | -1.1918183 | 1264.55971 | ml |
| ## 89 | -1.1110102 | 1256.69388 | ml |
| ## 90 | -1.0302021 | 1249.32722 | ml |
| ## 91 | -0.9493940 | 1242.43994 | ml |
| ## 92 | -0.8685860 | 1236.01149 | ml |
| ## 93 | -0.7877779 | 1230.02086 | ml |
| ## 94 | -0.7069698 | 1224.44679 | ml |
| ## 95 | -0.6261617 | 1219.26799 | ml |
| ## 96 | -0.5453536 | 1214.46332 | ml |
| ## 97 | -0.4645456 | 1210.01194 | ml |
| ## 98 | -0.3837375 | 1205.89341 | ml |
| ## 99 | -0.3029294 | 1202.08785 | ml |
| ## 100 | -0.2221213 | 1198.57597 | ml |
| ## 101 | -8.2221213 | -73.59652 | true |
| ## 102 | -8.1413132 | 34.64001 | true |
| ## 103 | -8.0605052 | 138.11334 | true |
| ## 104 | -7.9796971 | 236.99201 | true |
| ## 105 | -7.8988890 | 331.43754 | true |
| ## 106 | -7.8180809 | 421.60473 | true |
| ## 107 | -7.7372728 | 507.64201 | true |
| ## 108 | -7.6564648 | 589.69172 | true |
| ## 109 | -7.5756567 | 667.89039 | true |
| ## 110 | -7.4948486 | 742.36906 | true |
| ## 111 | -7.4140405 | 813.25353 | true |
| ## 112 | -7.3332324 | 880.66465 | true |
| ## 113 | -7.2524244 | 944.71854 | true |

| | | | |
|--------|------------|------------|------|
| ## 114 | -7.1716163 | 1005.52694 | true |
| ## 115 | -7.0908082 | 1063.19734 | true |
| ## 116 | -7.0100001 | 1117.83331 | true |
| ## 117 | -6.9291920 | 1169.53470 | true |
| ## 118 | -6.8483839 | 1218.39787 | true |
| ## 119 | -6.7675759 | 1264.51590 | true |
| ## 120 | -6.6867678 | 1307.97880 | true |
| ## 121 | -6.6059597 | 1348.87372 | true |
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| ## 123 | -6.4443435 | 1423.29496 | true |
| ## 124 | -6.3635355 | 1456.98290 | true |
| ## 125 | -6.2827274 | 1488.42641 | true |
| ## 126 | -6.2019193 | 1517.70094 | true |
| ## 127 | -6.1211112 | 1544.88007 | true |
| ## 128 | -6.0403031 | 1570.03563 | true |
| ## 129 | -5.9594951 | 1593.23780 | true |
| ## 130 | -5.8786870 | 1614.55525 | true |
| ## 131 | -5.7978789 | 1634.05520 | true |
| ## 132 | -5.7170708 | 1651.80352 | true |
| ## 133 | -5.6362627 | 1667.86478 | true |
| ## 134 | -5.5554547 | 1682.30235 | true |
| ## 135 | -5.4746466 | 1695.17842 | true |
| ## 136 | -5.3938385 | 1706.55403 | true |
| ## 137 | -5.3130304 | 1716.48912 | true |
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| ## 139 | -5.1514142 | 1732.27216 | true |
| ## 140 | -5.0706062 | 1738.23462 | true |
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| ## 142 | -4.9089900 | 1746.57980 | true |
| ## 143 | -4.8281819 | 1749.07063 | true |
| ## 144 | -4.7473738 | 1750.51057 | true |
| ## 145 | -4.6665658 | 1750.95095 | true |
| ## 146 | -4.5857577 | 1750.44197 | true |
| ## 147 | -4.5049496 | 1749.03268 | true |
| ## 148 | -4.4241415 | 1746.77099 | true |
| ## 149 | -4.3433334 | 1743.70361 | true |
| ## 150 | -4.2625254 | 1739.87606 | true |
| ## 151 | -4.1817173 | 1735.33266 | true |
| ## 152 | -4.1009092 | 1730.11650 | true |
| ## 153 | -4.0201011 | 1724.26946 | true |
| ## 154 | -3.9392930 | 1717.83217 | true |
| ## 155 | -3.8584850 | 1710.84406 | true |
| ## 156 | -3.7776769 | 1703.34334 | true |
| ## 157 | -3.6968688 | 1695.36701 | true |
| ## 158 | -3.6160607 | 1686.95092 | true |
| ## 159 | -3.5352526 | 1678.12972 | true |
| ## 160 | -3.4544446 | 1668.93694 | true |
| ## 161 | -3.3736365 | 1659.40503 | true |
| ## 162 | -3.2928284 | 1649.56532 | true |
| ## 163 | -3.2120203 | 1639.44811 | true |
| ## 164 | -3.1312122 | 1629.08270 | true |
| ## 165 | -3.0504041 | 1618.49737 | true |
| ## 166 | -2.9695961 | 1607.71945 | true |
| ## 167 | -2.8887880 | 1596.77533 | true |


```
## 168 -2.8079799 1585.69047 true
## 169 -2.7271718 1574.48942 true
## 170 -2.6463637 1563.19584 true
## 171 -2.5655557 1551.83247 true
## 172 -2.4847476 1540.42121 true
## 173 -2.4039395 1528.98304 true
## 174 -2.3231314 1517.53807 true
## 175 -2.2423233 1506.10554 true
## 176 -2.1615153 1494.70380 true
## 177 -2.0807072 1483.35033 true
## 178 -1.9998991 1472.06174 true
## 179 -1.9190910 1460.85379 true
## 180 -1.8382829 1449.74139 true
## 181 -1.7574749 1438.73864 true
## 182 -1.6766668 1427.85881 true
## 183 -1.5958587 1417.11441 true
## 184 -1.5150506 1406.51718 true
## 185 -1.4342425 1396.07812 true
## 186 -1.3534345 1385.80754 true
## 187 -1.2726264 1375.71507 true
## 188 -1.1918183 1365.80969 true
## 189 -1.1110102 1356.09974 true
## 190 -1.0302021 1346.59295 true
## 191 -0.9493940 1337.29645 true
## 192 -0.8685860 1328.21678 true
## 193 -0.7877779 1319.35991 true
## 194 -0.7069698 1310.73121 true
## 195 -0.6261617 1302.33551 true
## 196 -0.5453536 1294.17703 true
## 197 -0.4645456 1286.25941 true
## 198 -0.3837375 1278.58570 true
## 199 -0.3029294 1271.15835 true
## 200 -0.2221213 1263.97921 true
```

```
# theta5
const <- 4
theta5.v <- seq(ML.optim$par[5] - const,
               ML.optim$par[5] + const, length.out = 100)
plotl.th5 <- topplot.univ.comp(theta5.v, 5, 'theta5', t.parms, ML.optim$par,
                              ss2, M0 = 2.5, Tlim = 10)

multiplot(plotlist = plotl.th5, cols = 2)
```



| ## | x | y | typ |
|-------|-------------|--------------|-----|
| ## 1 | -4.05306828 | 1.349580e+03 | m1 |
| ## 2 | -3.97226020 | 1.349973e+03 | m1 |
| ## 3 | -3.89145212 | 1.350400e+03 | m1 |
| ## 4 | -3.81064404 | 1.350865e+03 | m1 |
| ## 5 | -3.72983596 | 1.351371e+03 | m1 |
| ## 6 | -3.64902788 | 1.351923e+03 | m1 |
| ## 7 | -3.56821980 | 1.352524e+03 | m1 |
| ## 8 | -3.48741172 | 1.353179e+03 | m1 |
| ## 9 | -3.40660364 | 1.353893e+03 | m1 |
| ## 10 | -3.32579556 | 1.354673e+03 | m1 |
| ## 11 | -3.24498748 | 1.355524e+03 | m1 |
| ## 12 | -3.16417939 | 1.356454e+03 | m1 |
| ## 13 | -3.08337131 | 1.357469e+03 | m1 |
| ## 14 | -3.00256323 | 1.358581e+03 | m1 |
| ## 15 | -2.92175515 | 1.359796e+03 | m1 |
| ## 16 | -2.84094707 | 1.361128e+03 | m1 |
| ## 17 | -2.76013899 | 1.362588e+03 | m1 |
| ## 18 | -2.67933091 | 1.364189e+03 | m1 |
| ## 19 | -2.59852283 | 1.365946e+03 | m1 |
| ## 20 | -2.51771475 | 1.367878e+03 | m1 |
| ## 21 | -2.43690667 | 1.370003e+03 | m1 |
| ## 22 | -2.35609859 | 1.372343e+03 | m1 |
| ## 23 | -2.27529051 | 1.374923e+03 | m1 |
| ## 24 | -2.19448242 | 1.377771e+03 | m1 |
| ## 25 | -2.11367434 | 1.380919e+03 | m1 |
| ## 26 | -2.03286626 | 1.384403e+03 | m1 |

| | | | |
|-------|-------------|---------------|----|
| ## 27 | -1.95205818 | 1.388264e+03 | m1 |
| ## 28 | -1.87125010 | 1.392548e+03 | m1 |
| ## 29 | -1.79044202 | 1.397311e+03 | m1 |
| ## 30 | -1.70963394 | 1.402612e+03 | m1 |
| ## 31 | -1.62882586 | 1.408522e+03 | m1 |
| ## 32 | -1.54801778 | 1.415121e+03 | m1 |
| ## 33 | -1.46720970 | 1.422499e+03 | m1 |
| ## 34 | -1.38640162 | 1.430761e+03 | m1 |
| ## 35 | -1.30559354 | 1.440024e+03 | m1 |
| ## 36 | -1.22478546 | 1.450420e+03 | m1 |
| ## 37 | -1.14397737 | 1.462097e+03 | m1 |
| ## 38 | -1.06316929 | 1.475218e+03 | m1 |
| ## 39 | -0.98236121 | 1.489959e+03 | m1 |
| ## 40 | -0.90155313 | 1.506503e+03 | m1 |
| ## 41 | -0.82074505 | 1.525031e+03 | m1 |
| ## 42 | -0.73993697 | 1.545707e+03 | m1 |
| ## 43 | -0.65912889 | 1.568645e+03 | m1 |
| ## 44 | -0.57832081 | 1.593867e+03 | m1 |
| ## 45 | -0.49751273 | 1.621222e+03 | m1 |
| ## 46 | -0.41670465 | 1.650267e+03 | m1 |
| ## 47 | -0.33589657 | 1.680071e+03 | m1 |
| ## 48 | -0.25508849 | 1.708901e+03 | m1 |
| ## 49 | -0.17428040 | 1.733713e+03 | m1 |
| ## 50 | -0.09347232 | 1.749313e+03 | m1 |
| ## 51 | -0.01266424 | 1.746949e+03 | m1 |
| ## 52 | 0.06814384 | 1.711867e+03 | m1 |
| ## 53 | 0.14895192 | 1.618972e+03 | m1 |
| ## 54 | 0.22976000 | 1.424860e+03 | m1 |
| ## 55 | 0.31056808 | 1.052674e+03 | m1 |
| ## 56 | 0.39137616 | 3.623072e+02 | m1 |
| ## 57 | 0.47218424 | -9.105104e+02 | m1 |
| ## 58 | 0.55299232 | -3.283863e+03 | m1 |
| ## 59 | 0.63380040 | -7.817862e+03 | m1 |
| ## 60 | 0.71460848 | -1.678616e+04 | m1 |
| ## 61 | 0.79541657 | -3.532200e+04 | m1 |
| ## 62 | 0.87622465 | -7.568118e+04 | m1 |
| ## 63 | 0.95703273 | -1.689588e+05 | m1 |
| ## 64 | 1.03784081 | -3.994372e+05 | m1 |
| ## 65 | 1.11864889 | -1.012569e+06 | m1 |
| ## 66 | 1.19945697 | -2.781191e+06 | m1 |
| ## 67 | 1.28026505 | -8.354082e+06 | m1 |
| ## 68 | 1.36107313 | -2.768653e+07 | m1 |
| ## 69 | 1.44188121 | -1.021417e+08 | m1 |
| ## 70 | 1.52268929 | -4.233863e+08 | m1 |
| ## 71 | 1.60349737 | -1.991464e+09 | m1 |
| ## 72 | 1.68430545 | -1.074351e+10 | m1 |
| ## 73 | 1.76511353 | -6.724710e+10 | m1 |
| ## 74 | 1.84592162 | -4.945263e+11 | m1 |
| ## 75 | 1.92672970 | -4.330966e+12 | m1 |
| ## 76 | 2.00753778 | -4.584018e+13 | m1 |
| ## 77 | 2.08834586 | -5.957965e+14 | m1 |
| ## 78 | 2.16915394 | -9.674901e+15 | m1 |
| ## 79 | 2.24996202 | -2.000003e+17 | m1 |
| ## 80 | 2.33077010 | -5.371233e+18 | m1 |

```

## 81 2.41157818 -1.915765e+20 ml
## 82 2.49238626 -9.294093e+21 ml
## 83 2.57319434 -6.293787e+23 ml
## 84 2.65400242 -6.118538e+25 ml
## 85 2.73481050 -8.802989e+27 ml
## 86 2.81561859 -1.937261e+30 ml
## 87 2.89642667 -6.758584e+32 ml
## 88 2.97723475 -3.885752e+35 ml
## 89 3.05804283 -3.839771e+38 ml
## 90 3.13885091 -6.825627e+41 ml
## 91 3.21965899 -2.293236e+45 ml
## 92 3.30046707 -1.536359e+49 ml
## 93 3.38127515 -2.175207e+53 ml
## 94 3.46208323 -6.931427e+57 ml
## 95 3.54289131 -5.322439e+62 ml
## 96 3.62369939 -1.060503e+68 ml
## 97 3.70450747 -5.941268e+73 ml
## 98 3.78531556 -1.020937e+80 ml
## 99 3.86612364 -5.913400e+86 ml
## 100 3.94693172 -1.278818e+94 ml
## 101 -4.05306828 1.560143e+03 true
## 102 -3.97226020 1.560791e+03 true
## 103 -3.89145212 1.561494e+03 true
## 104 -3.81064404 1.562257e+03 true
## 105 -3.72983596 1.563087e+03 true
## 106 -3.64902788 1.563989e+03 true
## 107 -3.56821980 1.564969e+03 true
## 108 -3.48741172 1.566034e+03 true
## 109 -3.40660364 1.567193e+03 true
## 110 -3.32579556 1.568453e+03 true
## 111 -3.24498748 1.569824e+03 true
## 112 -3.16417939 1.571315e+03 true
## 113 -3.08337131 1.572938e+03 true
## 114 -3.00256323 1.574704e+03 true
## 115 -2.92175515 1.576628e+03 true
## 116 -2.84094707 1.578722e+03 true
## 117 -2.76013899 1.581003e+03 true
## 118 -2.67933091 1.583489e+03 true
## 119 -2.59852283 1.586197e+03 true
## 120 -2.51771475 1.589149e+03 true
## 121 -2.43690667 1.592367e+03 true
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## 123 -2.27529051 1.599698e+03 true
## 124 -2.19448242 1.603867e+03 true
## 125 -2.11367434 1.608410e+03 true
## 126 -2.03286626 1.613360e+03 true
## 127 -1.95205818 1.618750e+03 true
## 128 -1.87125010 1.624616e+03 true
## 129 -1.79044202 1.630991e+03 true
## 130 -1.70963394 1.637909e+03 true
## 131 -1.62882586 1.645401e+03 true
## 132 -1.54801778 1.653491e+03 true
## 133 -1.46720970 1.662194e+03 true
## 134 -1.38640162 1.671505e+03 true

```

```

## 135 -1.30559354 1.681396e+03 true
## 136 -1.22478546 1.691799e+03 true
## 137 -1.14397737 1.702588e+03 true
## 138 -1.06316929 1.713551e+03 true
## 139 -0.98236121 1.724350e+03 true
## 140 -0.90155313 1.734463e+03 true
## 141 -0.82074505 1.743099e+03 true
## 142 -0.73993697 1.749072e+03 true
## 143 -0.65912889 1.750610e+03 true
## 144 -0.57832081 1.745077e+03 true
## 145 -0.49751273 1.728528e+03 true
## 146 -0.41670465 1.695038e+03 true
## 147 -0.33589657 1.635625e+03 true
## 148 -0.25508849 1.536505e+03 true
## 149 -0.17428040 1.376218e+03 true
## 150 -0.09347232 1.120739e+03 true
## 151 -0.01266424 7.149823e+02 true
## 152 0.06814384 6.757582e+01 true
## 153 0.14895192 -9.772256e+02 true
## 154 0.22976000 -2.693095e+03 true
## 155 0.31056808 -5.577366e+03 true
## 156 0.39137616 -1.056778e+04 true
## 157 0.47218424 -1.950518e+04 true
## 158 0.55299232 -3.616554e+04 true
## 159 0.63380040 -6.867307e+04 true
## 160 0.71460848 -1.354387e+05 true
## 161 0.79541657 -2.806050e+05 true
## 162 0.87622465 -6.166935e+05 true
## 163 0.95703273 -1.450256e+06 true
## 164 1.03784081 -3.679044e+06 true
## 165 1.11864889 -1.014697e+07 true
## 166 1.19945697 -3.066572e+07 true
## 167 1.28026505 -1.023780e+08 true
## 168 1.36107313 -3.808198e+08 true
## 169 1.44188121 -1.592865e+09 true
## 170 1.52268929 -7.566348e+09 true
## 171 1.60349737 -4.125687e+10 true
## 172 1.68430545 -2.612476e+11 true
## 173 1.76511353 -1.945453e+12 true
## 174 1.84592162 -1.727144e+13 true
## 175 1.92672970 -1.855243e+14 true
## 176 2.00753778 -2.450211e+15 true
## 177 2.08834586 -4.048450e+16 true
## 178 2.16915394 -8.527948e+17 true
## 179 2.24996202 -2.337478e+19 true
## 180 2.33077010 -8.523577e+20 true
## 181 2.41157818 -4.235467e+22 true
## 182 2.49238626 -2.943729e+24 true
## 183 2.57319434 -2.943578e+26 true
## 184 2.65400242 -4.366470e+28 true
## 185 2.73481050 -9.932946e+30 true
## 186 2.81561859 -3.592085e+33 true
## 187 2.89642667 -2.147236e+36 true
## 188 2.97723475 -2.213336e+39 true

```

```
## 189 3.05804283 -4.118749e+42 true
## 190 3.13885091 -1.454205e+46 true
## 191 3.21965899 -1.028105e+50 true
## 192 3.30046707 -1.543050e+54 true
## 193 3.38127515 -5.238044e+58 true
## 194 3.46208323 -4.307604e+63 true
## 195 3.54289131 -9.245318e+68 true
## 196 3.62369939 -5.614243e+74 true
## 197 3.70450747 -1.052831e+81 true
## 198 3.78531556 -6.704079e+87 true
## 199 3.86612364 -1.606627e+95 true
## 200 3.94693172 -1.620058e+103 true
```

```
# univariate likelihood analysis
```

```
toplot.loglambda.comp <- function(par.values, par.idx, par.name,
                                   theta.par, ML.est, Ht, M0, Tlim, tt = 5){

  theta.m.true <- cbind(rep(t.parms[1], length(par.values)),
                        rep(t.parms[2], length(par.values)),
                        rep(t.parms[3], length(par.values)),
                        rep(t.parms[4], length(par.values)),
                        rep(t.parms[5], length(par.values)))

  theta.m.ML <- cbind(rep(ML.est[1], length(par.values)),
                     rep(ML.est[2], length(par.values)),
                     rep(ML.est[3], length(par.values)),
                     rep(ML.est[4], length(par.values)),
                     rep(ML.est[5], length(par.values)))

  theta.m.true[,par.idx] <- par.values
  theta.m.ML[,par.idx] <- par.values

  LL.true <- sapply(1:nrow(theta.m.true), function(i)
    log.lambda.ETAS.single(tt, theta.m.true[i,], Ht, M0))

  LL.ML <- sapply(1:nrow(theta.m.ML), function(i)
    log.lambda.ETAS.single(tt, theta.m.ML[i,], Ht, M0))

  ll.lim <- range(c(LL.true, LL.ML))

  df <- rbind(data.frame(x = par.values,
                        y = LL.ML,
                        typ = 'ml'),
              data.frame(x = par.values,
                        y = LL.true,
                        typ = 'true'))

  list(pl.true = ggplot(data.frame(x = par.values,
                                   y = LL.true), aes(x = x, y = y)) +
    geom_line() +
    geom_vline(xintercept = ML.est[par.idx], linetype = 2) +
    labs(title = 'true params') +
    ylab('log-lambda') +
```

```

    xlab(par.name) +
    ylim(ll.lim),
    pl.ML = ggplot(data.frame(x = par.values,
                              y = LL.ML), aes(x = x, y = y)) +

    geom_line() +
    geom_vline(xintercept = ML.est[par.idx], linetype = 2)+
    labs(title = 'ML est')+
    ylab('log-lambda') +
    xlab(par.name) +
    ylim(ll.lim),
    df = df)
}

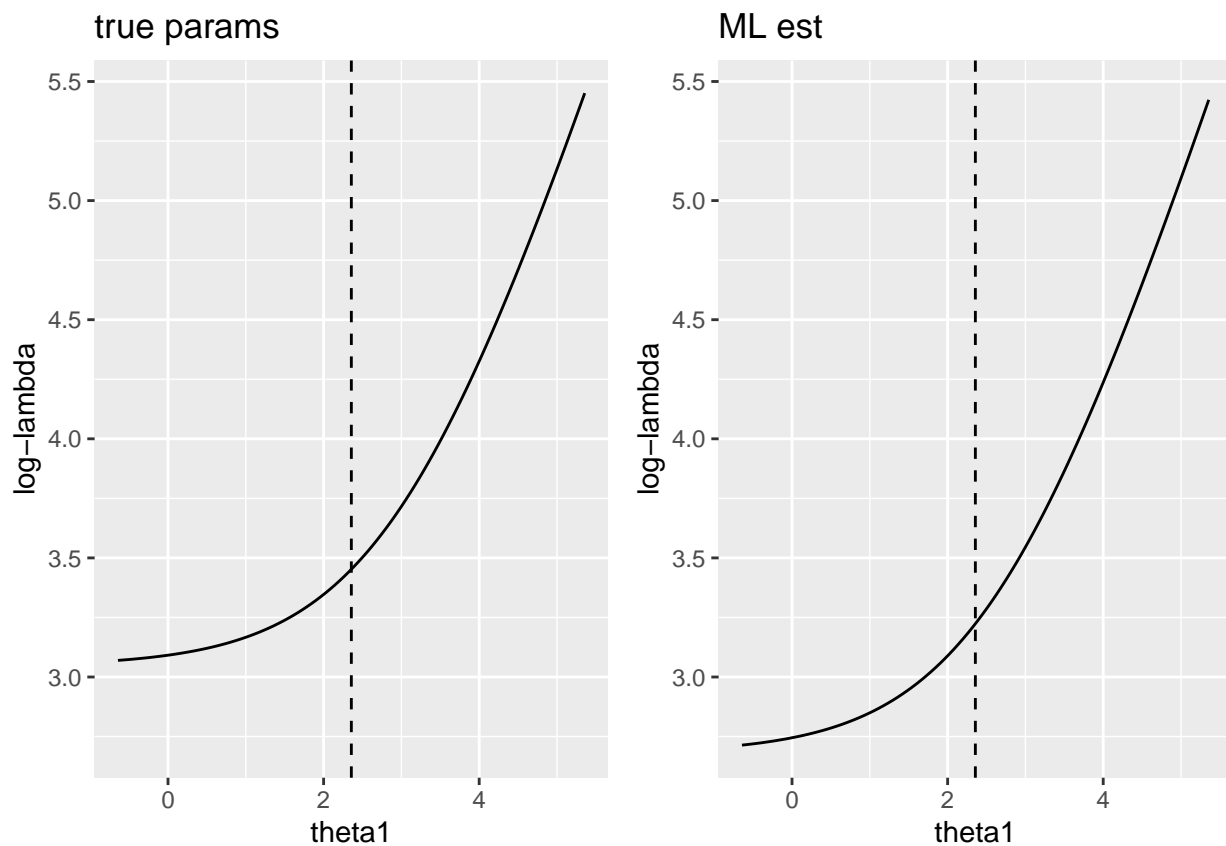
```

```

# theta1
# const <- 4
# theta1.v <- seq(ML.optim$par[4] - const,
#                 ML.optim$par[4] + const, length.out = 100)
plotllambda.th1 <- toplot.loglambda.comp(theta1.v, 1, 'theta1',
    theta.par = t.parms,
    ML.est = ML.optim$par,
    ss2, MO = 2.5, Tlim = 10)

multiplot(plotlist = plotllambda.th1[1:2], cols = 2)

```



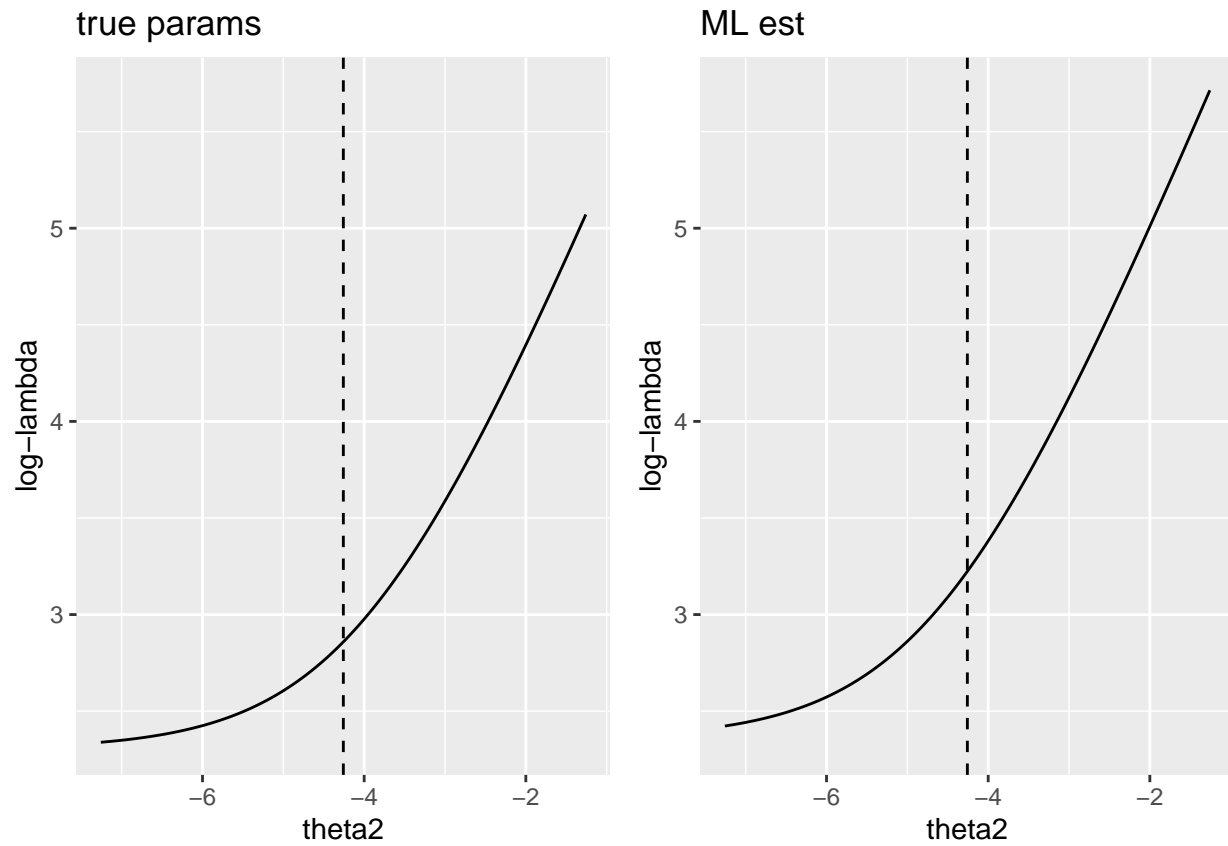
```

plotllambda.th2 <- toplot.loglambda.comp(theta2.v, 2, 'theta2',
    theta.par = t.parms,
    ML.est = ML.optim$par,

```

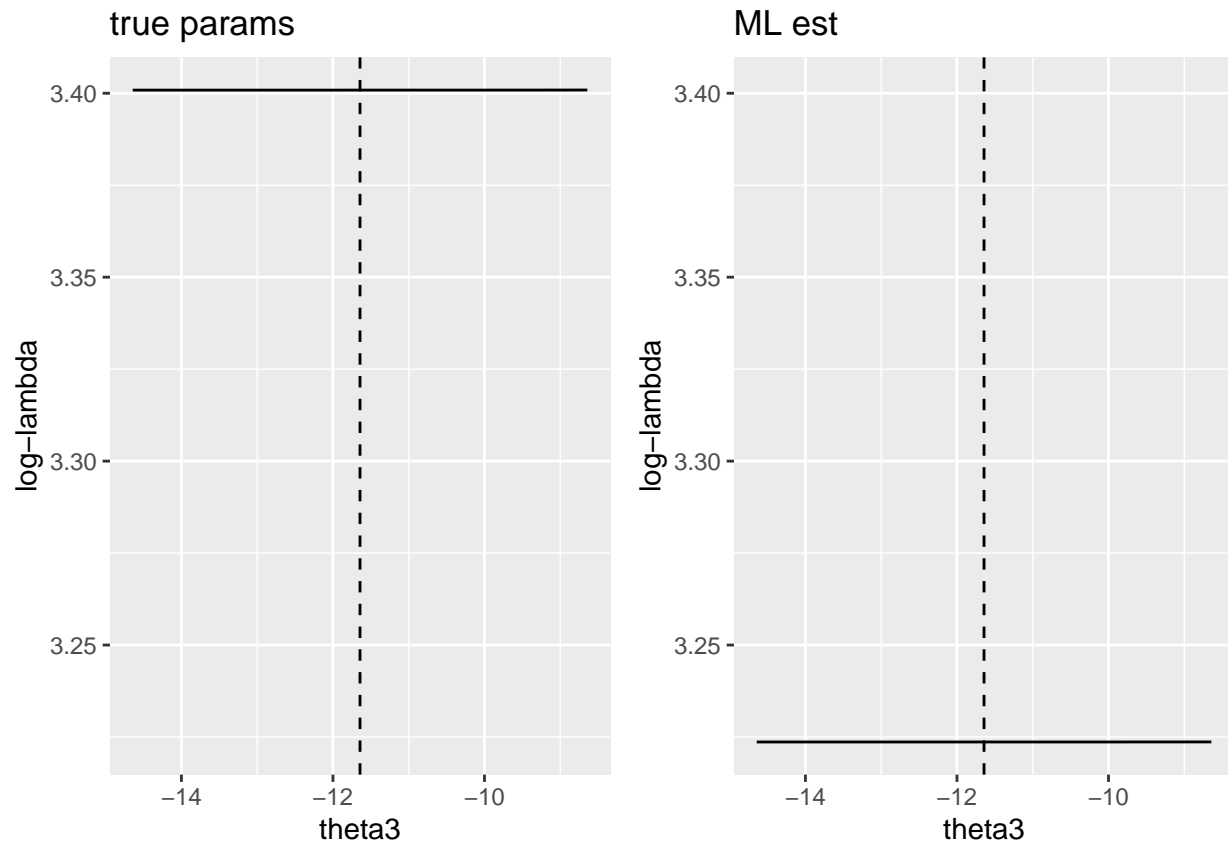
```
ss2, M0 = 2.5, Tlim = 10)
```

```
multiplot(plotlist = plotllambda.th2[1:2], cols = 2)
```



```
plotllambda.th3 <- toplot.loglambda.comp(theta3.v, 3, 'theta3',
  theta.par = t.parms,
  ML.est = ML.optim$par,
  ss2, M0 = 2.5, Tlim = 10)
```

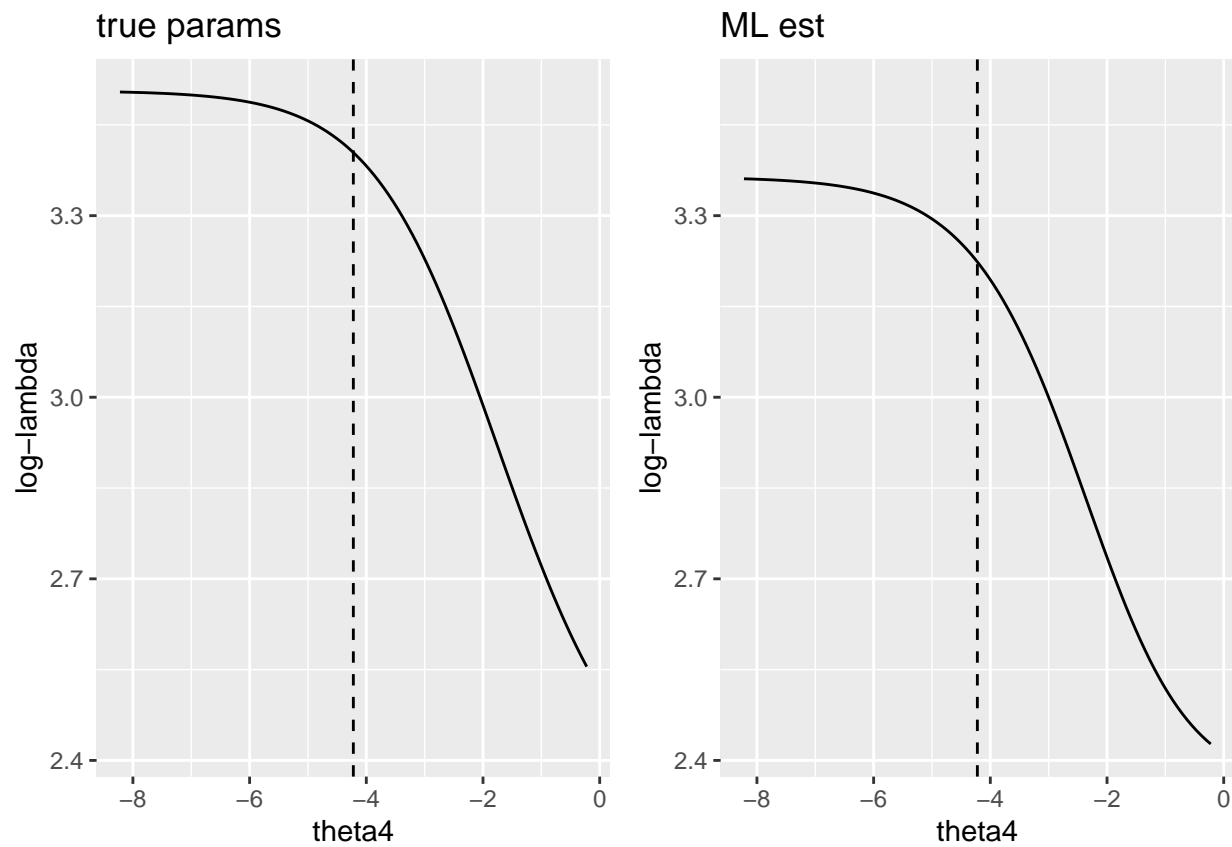
```
multiplot(plotlist = plotllambda.th3[1:2], cols = 2)
```

```
#plot(plotllambda.th3$df$x[plotllambda.th3$df$typ == 'ml'],
#      plotllambda.th3$df$y[plotllambda.th3$df$typ == 'ml'])

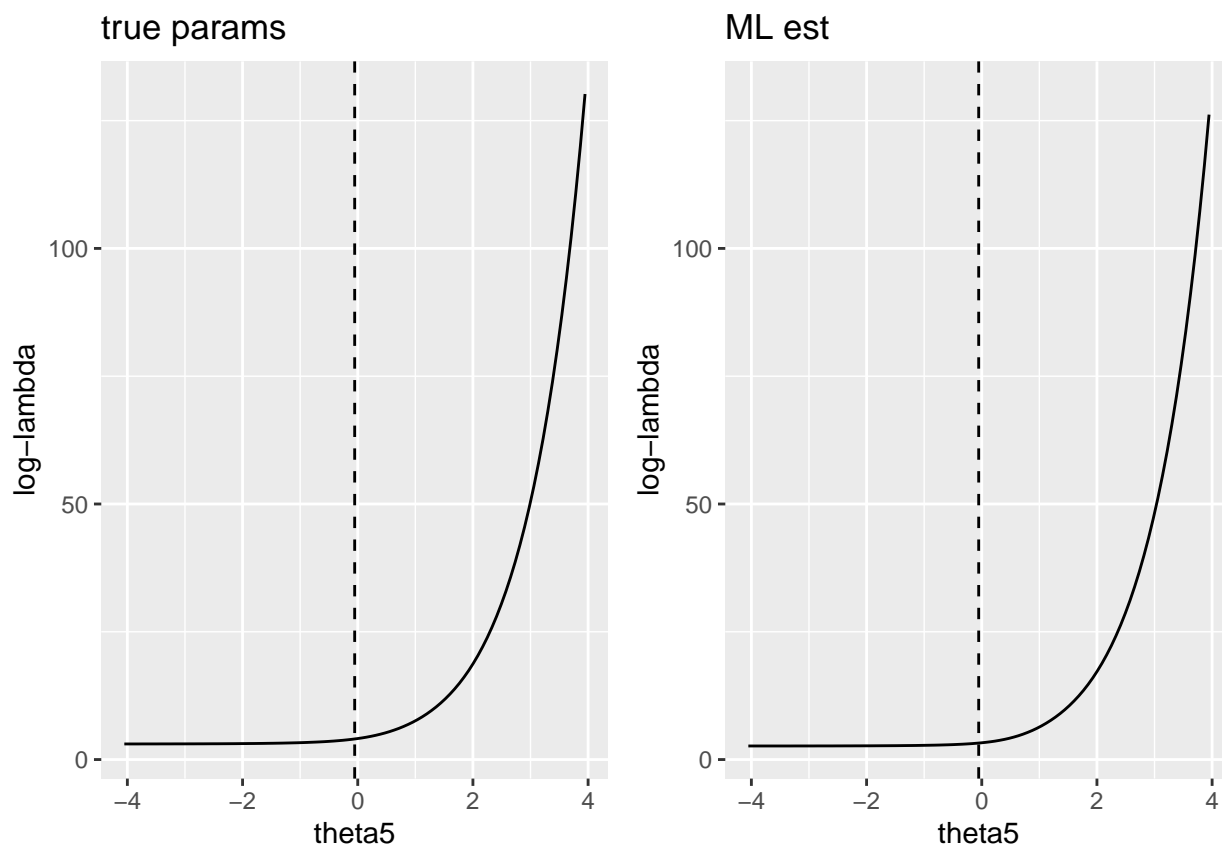
plotllambda.th4 <- toplot.loglambda.comp(theta4.v, 4, 'theta4',
                                         theta.par = t.parms,
                                         ML.est = ML.optim$par,
                                         ss2, MO = 2.5, Tlim = 10)

multiplot(plotlist = plotllambda.th4[1:2], cols = 2)
```



```
plotllambda.th5 <- topplot.loglambda.comp(theta5.v, 5, 'theta5',
  theta.par = t.parms,
  ML.est = ML.optim$par,
  ss2, M0 = 2.5, Tlim = 10)

multiplot(plotlist = plotllambda.th5[1:2], cols = 2)
```



```
lin.loglambda.th1 <-
  topplot.loglambda.lin.comp(theta1.v, 1, 'theta1', ML.optim$par[1],
    ML.optim$par, ss2, M0 = 2.5, Tlim = 10,
    derFUN.list = list(log.lambda.der.th1,
      log.lambda.der.th2,
      log.lambda.der.th3,
      log.lambda.der.th4,
      log.lambda.der.th5))
```

```
lin.loglambda.th2 <-
  topplot.loglambda.lin.comp(theta2.v, 2, 'theta2', ML.optim$par[2],
    ML.optim$par, ss2, M0 = 2.5, Tlim = 10,
    derFUN.list = list(log.lambda.der.th1,
      log.lambda.der.th2,
      log.lambda.der.th3,
      log.lambda.der.th4,
      log.lambda.der.th5))
```

```
lin.loglambda.th3 <-
  topplot.loglambda.lin.comp(theta3.v, 3, 'theta3', ML.optim$par[3],
    ML.optim$par, ss2, M0 = 2.5, Tlim = 10,
    derFUN.list = list(log.lambda.der.th1,
      log.lambda.der.th2,
      log.lambda.der.th3,
      log.lambda.der.th4,
```

```

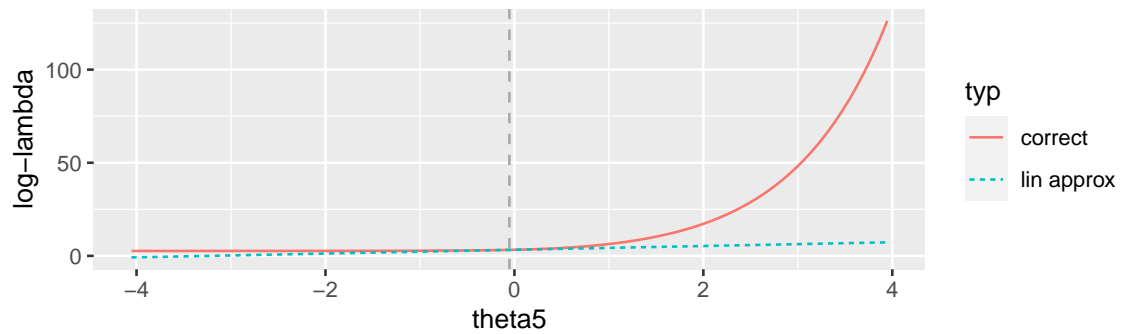
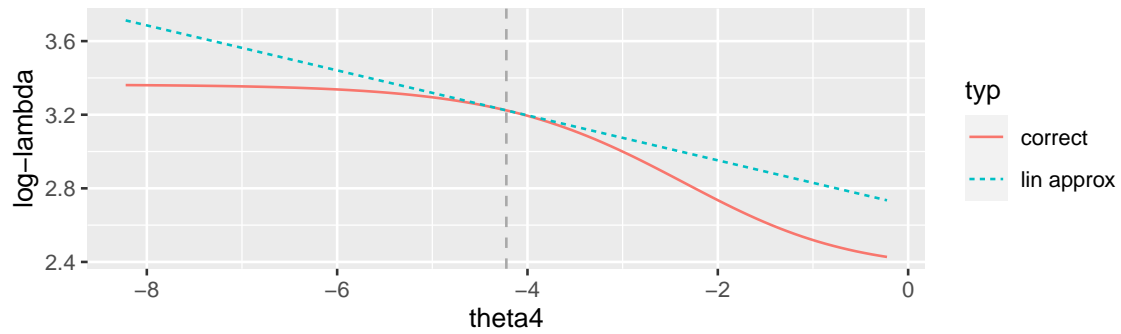
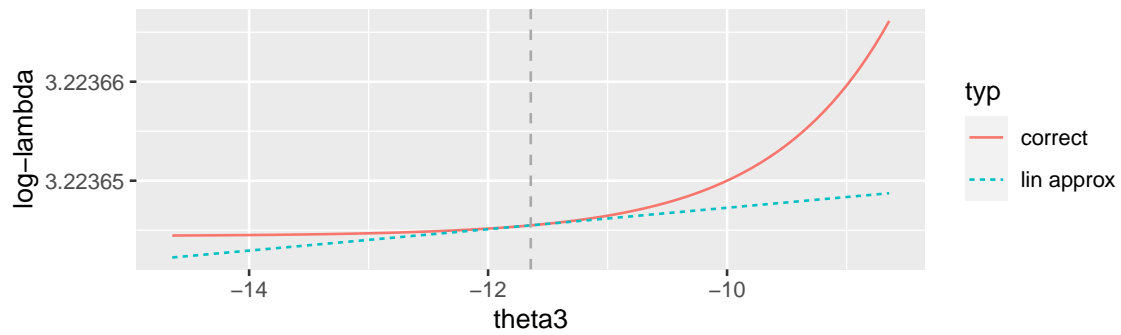
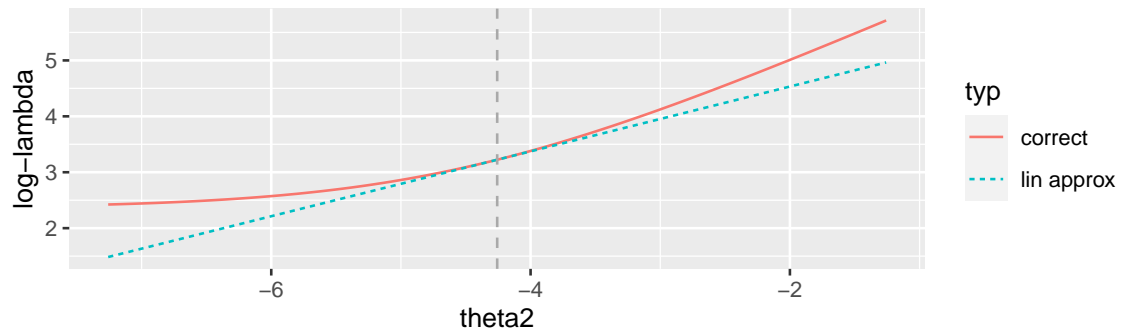
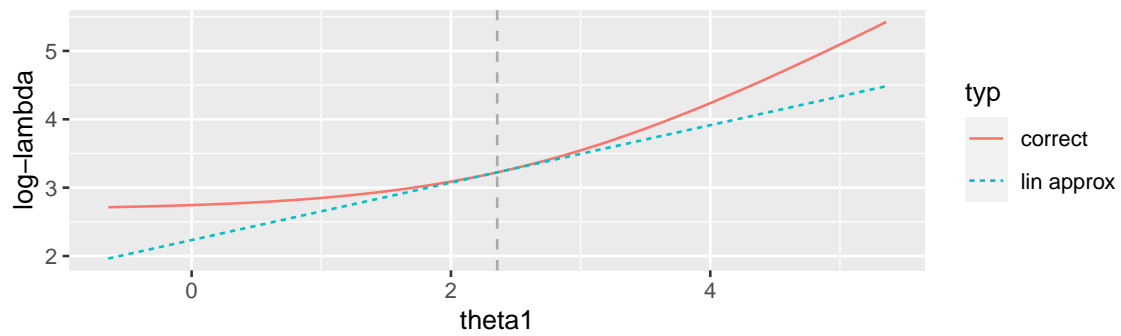
log.lambda.der.th5))

lin.loglambda.th4 <-
  topplot.loglambda.lin.comp(theta4.v, 4, 'theta4', ML.optim$par[4],
    ML.optim$par, ss2, M0 = 2.5, Tlim = 10,
    derFUN.list = list(log.lambda.der.th1,
                        log.lambda.der.th2,
                        log.lambda.der.th3,
                        log.lambda.der.th4,
                        log.lambda.der.th5))

lin.loglambda.th5 <-
  topplot.loglambda.lin.comp(theta5.v, 5, 'theta5', ML.optim$par[5],
    ML.optim$par, ss2, M0 = 2.5, Tlim = 10,
    derFUN.list = list(log.lambda.der.th1,
                        log.lambda.der.th2,
                        log.lambda.der.th3,
                        log.lambda.der.th4,
                        log.lambda.der.th5))

multiplot(lin.loglambda.th1$pl,
  lin.loglambda.th2$pl,
  lin.loglambda.th3$pl,
  lin.loglambda.th4$pl,
  lin.loglambda.th5$pl)

```



```
pl.theta1 <- topplot.loglik.lin.comp(theta1.v, 1, 'theta1', ML.optim$par, ss2, M0 = 2.5,
                                     Tlim, ML.optim$par,
                                     by.s = 0.1)
```

```
## [1] 100
```

```
pl.theta2 <- topplot.loglik.lin.comp(theta2.v, 2, 'theta2', ML.optim$par, ss2, M0 = 2.5,
                                     Tlim, ML.optim$par,
                                     by.s = 0.1)
```

```
## [1] 100
```

```
pl.theta3 <- topplot.loglik.lin.comp(theta3.v, 3, 'theta3', ML.optim$par, ss2, M0 = 2.5,
                                     Tlim, ML.optim$par,
                                     by.s = 0.1)
```

```
## [1] 100
```

```
pl.theta4 <- topplot.loglik.lin.comp(theta4.v, 4, 'theta4', ML.optim$par, ss2, M0 = 2.5,
                                     Tlim, ML.optim$par,
                                     by.s = 0.1)
```

```
## [1] 100
```

```
pl.theta5 <- topplot.loglik.lin.comp(theta5.v, 5, 'theta5', ML.optim$par, ss2, M0 = 2.5,
                                     Tlim, ML.optim$par,
                                     by.s = 0.1)
```

```
## [1] 100
```

```
multiplot(pl.theta1,
          pl.theta2,
          pl.theta3,
          pl.theta4,
          pl.theta5)
```

