## SurvGPR Vignette

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In this document, we show how to use the SurvGPR R package. First, we download the package from github.com/ajmolstad/SurvGRP.

```
library(devtools)
devtools::install_github("ajmolstad/SurvGPR")
```

Then, we create survival data from the Gaussian process regression model.

```
sessionInfo()
```

```
## R version 3.5.2 (2018-12-20)
## Platform: x86_64-apple-darwin15.6.0 (64-bit)
## Running under: macOS High Sierra 10.13.6
##
## Matrix products: default
## BLAS: /Library/Frameworks/R.framework/Versions/3.5/Resources/lib/libRblas.0.dylib
## LAPACK: /Library/Frameworks/R.framework/Versions/3.5/Resources/lib/libRlapack.dylib
##
## locale:
## [1] en_US.UTF-8/en_US.UTF-8/en_US.UTF-8/C/en_US.UTF-8/en_US.UTF-8
## attached base packages:
## [1] stats
                  graphics grDevices utils
                                                 datasets methods
                                                                      base
##
## loaded via a namespace (and not attached):
## [1] compiler_3.5.2 magrittr_1.5
                                          tools_3.5.2
                                                           htmltools 0.3.6
## [5] yaml_2.2.0
                         Rcpp_1.0.1
                                          stringi_1.3.1
                                                           rmarkdown 1.11
## [9] knitr_1.21
                         stringr_1.4.0
                                          xfun_0.5
                                                           digest_0.6.18
## [13] evaluate_0.13
library(SurvGPR)
library(MASS)
# set dimesions
set.seed(20)
n = 500
p = 1000
q = 2
train.inds <- sample(1:n, 300)</pre>
test.inds <- c(1:n)[-train.inds]</pre>
# generate gene expression kernel
SigmaX <- matrix(.5, nrow=p, ncol=p)</pre>
diag(SigmaX) <- 1</pre>
X <- mvrnorm(n = n, mu = rep(0, p), Sigma = SigmaX, tol = 1e-6)
Kout <- as.matrix(dist(X, method="euclidean"))</pre>
K1 <- exp(-Kout/max(Kout[train.inds, train.inds]))</pre>
K1.full <- exp(-Kout/max(Kout))</pre>
Z <- cbind(rep(1, n), matrix(rnorm(n*q), nrow=n))</pre>
```

```
beta <- c(6.2, -0.5, -1.2)
Sigma <- 3*K1.full
G <- mvrnorm(n = 1, mu = rep(0, n), Sigma = Sigma, tol = 1e-6)

# generate failure times
log_time <- Z%*%beta + c(G) + rnorm(n, sd=sqrt(.5))
C <- log(rexp(n=n, rate=1/quantile(exp(log_time), .8)))
y <- pmin(log_time, C)
time <- exp(y)
status <- 1*(y != C)</pre>
```

Next, we fit the SurvGPR model using the following. Please note that this may take a few minutes to run.

```
## 1 : ASE = 0.126 ; sigma2 = 2.72 ; resid = 10.73897 ; sk = 500
## 2 : ASE = 0.031; sigma2 = 2.903; resid = 0.93703; sk = 500
## 3 : ASE = 0.01 ; sigma2 = 2.973 ; resid = 0.0903 ; sk = 500
## 4 : ASE = 0.006 ; sigma2 = 2.974 ; resid = 0.00503 ; sk = 500
## 5 : ASE = 0.001; sigma2 = 3.008; resid = -0.00043; sk = 500
## Adding samples for ascent: 1000 samples
## 5 : ASE = 0.001 ; sigma2 = 3.023 ; resid = 0.00092 ; sk = 1000
## 6 : ASE = 0.001 ; sigma2 = 3.033 ; resid = -0.00036 ; sk = 1000
## Adding samples for ascent: 2000 samples
## 6 : ASE = 0.001 ; sigma2 = 3.033 ; resid = -0.00041 ; sk = 2000
## Adding samples for ascent: 4000 samples
## 6 : ASE = 0 ; sigma2 = 3.034 ; resid = 0.00028 ; sk = 4000
## 7 : ASE = 0 ; sigma2 = 3.032 ; resid = -0.00019 ; sk = 4000
## Adding samples for ascent: 8000 samples
## 7 : ASE = 0 ; sigma2 = 3.036 ; resid = -2e-05 ; sk = 8000
## Adding samples for ascent: 16000 samples
## 7 : ASE = 0 ; sigma2 = 3.037 ; resid = 0.00014 ; sk = 16000
## 8 : ASE = 0 ; sigma2 = 3.039 ; resid = 1e-05 ; sk = 16000
## Adding samples for ascent: 32000 samples
## 8 : ASE = 0 ; sigma2 = 3.041 ; resid = 7e-05 ; sk = 32000
## Adding samples for ascent: 64000 samples
## 8 : ASE = 0 ; sigma2 = 3.042 ; resid = 0.00012 ; sk = 64000
## 9 : ASE = 0 ; sigma2 = 3.042 ; resid = 0 ; sk = 64000
## Adding samples for ascent: 128000 samples
```

We can look at the estimated variance components:

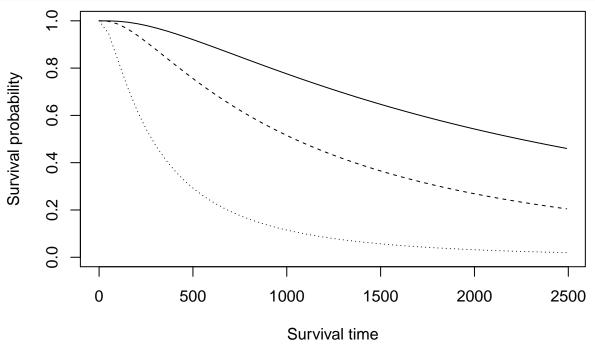
```
results$sigma2
```

```
## [1] 3.0423070 0.4677258
```

Finally, we can then predict for new subjects. Note that we can also get predicted survival probabilities at certain times (on the original scale, not log-scale) by specifying times int he times argument.

```
## List of 3
## $ test.inds: int [1:200] 4 6 7 12 13 21 23 25 29 40 ...
## $ log.pred : num [1:200, 1] 7.71 6.95 5.64 5.34 3.76 ...
## $ survFunc : num [1:200, 1:50] 1 1 1 1 1 1 1 1 1 ...
```

The output contains the predicted survival times on the log-scale, the testing indices, and the survival probabilities for all test set patients at the values given for times. We plot the estimated probabilities for three different subjects below.



We also plot our predictions versus the true log-survival times.

```
plot(x = pred_results$log.pred, y = log_time[pred_results$test.inds], xlab = "Predicted log-survival times", pch = 20)
abline(0, 1, lty = 2)
```

