Gaussian_Process_Code

Chiwan Kim 2/3/2020

```
##Part 1: Standard Gaussian Process
1-1: Fitting
library(rstan)
## Loading required package: StanHeaders
## Loading required package: ggplot2
## rstan (Version 2.19.2, GitRev: 2e1f913d3ca3)
## For execution on a local, multicore CPU with excess RAM we recommend calling
## options(mc.cores = parallel::detectCores()).
## To avoid recompilation of unchanged Stan programs, we recommend calling
## rstan_options(auto_write = TRUE)
## For improved execution time, we recommend calling
## Sys.setenv(LOCAL_CPPFLAGS = '-march=native')
## although this causes Stan to throw an error on a few processors.
source("gp.utility.R")
# Fitting GP model
stan_dat <- read_rdump('Financial_Data_Put_American.R')</pre>
##
## 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
## Loading required package: limSolve
## Attaching package: 'limSolve'
## The following object is masked from 'package:ggplot2':
##
##
       resolution
```

```
## Loading required package: futile.logger
## Welcome to ragtop. Logging can be enabled with commands such as
     futile.logger::flog.threshold(futile.logger::INFO, name='ragtop.calibration')
## Parsed with column specification:
## cols(
##
     .default = col double(),
##
     date = col_character(),
##
     symbol = col_character(),
##
     exdate = col_character(),
     cp_flag = col_character(),
##
##
    ticker = col_character(),
##
    exercise style = col character()
## )
## See spec(...) for full column specifications.
fit_gp_SGP_American <- stan(file="gp-fit-6dimension_withBS.stan", data=stan_dat,
               iter=100, chains=1);
## DIAGNOSTIC(S) FROM PARSER:
## Info: Comments beginning with # are deprecated. Please use // in place of # for line comments.
## SAMPLING FOR MODEL 'gp-fit-6dimension_withBS' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0.091 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would take 910 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: WARNING: There aren't enough warmup iterations to fit the
                     three stages of adaptation as currently configured.
## Chain 1:
## Chain 1:
                     Reducing each adaptation stage to 15%/75%/10% of
## Chain 1:
                     the given number of warmup iterations:
## Chain 1:
                       init buffer = 7
## Chain 1:
                       adapt_window = 38
## Chain 1:
                       term_buffer = 5
## Chain 1:
## Chain 1: Iteration: 1 / 100 [ 1%]
                                         (Warmup)
## Chain 1: Iteration: 10 / 100 [ 10%]
                                         (Warmup)
## Chain 1: Iteration: 20 / 100 [ 20%]
                                         (Warmup)
## Chain 1: Iteration: 30 / 100 [ 30%]
                                         (Warmup)
## Chain 1: Iteration: 40 / 100 [ 40%]
                                         (Warmup)
## Chain 1: Iteration: 50 / 100 [ 50%]
                                         (Warmup)
## Chain 1: Iteration: 51 / 100 [ 51%]
                                         (Sampling)
## Chain 1: Iteration: 60 / 100 [ 60%]
                                         (Sampling)
## Chain 1: Iteration: 70 / 100 [ 70%]
                                         (Sampling)
## Chain 1: Iteration: 80 / 100 [ 80%]
                                         (Sampling)
## Chain 1: Iteration: 90 / 100 [ 90%]
                                         (Sampling)
## Chain 1: Iteration: 100 / 100 [100%]
                                         (Sampling)
## Chain 1:
```

```
## Chain 1:
                            77.141 seconds (Sampling)
## Chain 1:
                            164.604 seconds (Total)
## Chain 1:
print(fit_gp_SGP_American, pars = c('theta', 'sigma2', 'gamma2'))
## Inference for Stan model: gp-fit-6dimension_withBS.
## 1 chains, each with iter=100; warmup=50; thin=1;
## post-warmup draws per chain=50, total post-warmup draws=50.
##
##
               mean se mean
                                  sd
                                        2.5%
                                                  25%
                                                          50%
                                                                  75%
                                                                         97.5%
## theta[1]
               0.21
                        0.00
                                0.04
                                        0.15
                                                 0.19
                                                         0.21
                                                                  0.24
                                                                          0.30
## theta[2]
               1.28
                        0.05
                                0.31
                                        0.85
                                                 1.01
                                                         1.26
                                                                  1.46
                                                                          1.89
## theta[3]
              10.93
                        0.29
                                        7.33
                                                10.22
                                                        10.94
                                                                 12.09
                                                                         13.24
                                1.59
## theta[4]
               0.47
                        0.01
                                0.04
                                        0.42
                                                 0.45
                                                         0.47
                                                                 0.50
                                                                          0.55
## theta[5]
                       0.23
                                0.97
                                        0.64
                                                 0.83
                                                         1.07
                                                                 1.44
                                                                          4.82
               1.35
## theta[6]
              59.77
                        4.19
                               23.67
                                       26.21
                                                40.27
                                                        56.24
                                                                 76.32 107.83
                                                         0.00
                                                                 0.00
## sigma2
               0.00
                        0.00
                                0.00
                                        0.00
                                                 0.00
                                                                          0.00
            4120.24 285.30 1392.81 2211.36 3035.92 4000.25 4920.80 7022.30
## gamma2
##
            n eff Rhat
## theta[1]
               85 0.99
               39 0.99
## theta[2]
## theta[3]
               29 1.06
## theta[4]
               49 1.00
## theta[5]
               17 1.10
## theta[6]
               32 1.04
               38 0.98
## sigma2
## gamma2
               24 1.07
##
## Samples were drawn using NUTS(diag_e) at Fri Mar 27 21:58:43 2020.
## For each parameter, n_eff is a crude measure of effective sample size,
## and Rhat is the potential scale reduction factor on split chains (at
## convergence, Rhat=1).
sum_gp_SGP_American <- extract(fit_gp_SGP_American,permuted=FALSE)</pre>
# Predicting from GP model
post_mean_theta_1_SGP <- mean(sum_gp_SGP_American[,1,1]) #theta</pre>
post mean theta 2 SGP <- mean(sum gp SGP American[,1,2]) #theta
post_mean_theta_3_SGP <- mean(sum_gp_SGP_American[,1,3]) #theta</pre>
post_mean_theta_4_SGP <- mean(sum_gp_SGP_American[,1,4]) #theta</pre>
post_mean_theta_5_SGP <- mean(sum_gp_SGP_American[,1,5]) #theta</pre>
post_mean_theta_6_SGP <- mean(sum_gp_SGP_American[,1,6]) #theta</pre>
post_mean_sigma2_SGP <- mean(sum_gp_SGP_American[,1,7]) #sigma2</pre>
post_mean_gamma2_SGP <- mean(sum_gp_SGP_American[,1,8]) #gamma2</pre>
post_mean_mu_SGP <- stan_dat$blackscholes</pre>
test_start <- 323 #06/10
test_end <- 559 #06/14
# test start <- 560 #06/17
```

Chain 1: Elapsed Time: 87.463 seconds (Warm-up)

```
# test_end <- 852 #06/20
x.grid_1 <- as.numeric(stan_dat$total_puts_American$forward_price[test_start:test_end])</pre>
x.grid_2 <- as.numeric(stan_dat$total_puts_American$strike_price[test_start:test_end])</pre>
x.grid_3 <- as.numeric(stan_dat$total_puts_American$impl_volatility[test_start:test_end])</pre>
x.grid_4 <- as.numeric(stan_dat$total_puts_American$time_to_exp[test_start:test_end]*250)</pre>
x.grid_5 <- as.numeric(stan_dat$total_puts_American$dividend[test_start:test_end])</pre>
x.grid_6 <- as.numeric(stan_dat$total_puts_American$interest_rate[test_start:test_end])</pre>
x2 <- cbind(x.grid_1,x.grid_2,x.grid_3,x.grid_4,x.grid_5,x.grid_6)</pre>
library('qrmtools')
## Registered S3 method overwritten by 'xts':
             method
                                           from
##
             as.zoo.xts zoo
## Registered S3 method overwritten by 'quantmod':
##
             method
                                                             from
##
             as.zoo.data.frame zoo
library('ragtop')
blackscholes_2 <- rep(NA,length(x2[,1]))</pre>
for (row in 1:nrow(data.frame(x2))){
     blackscholes_2[row] <- as.numeric(blackscholes(-1,S0=x.grid_1[row],K=x.grid_2[row],r=x.grid_6[row],t=x.grid_1[row],r=x.grid_2[row],r=x.grid_1[row],t=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[row],r=x.grid_1[
     \# blackscholes_2[row] <- Black_Scholes(0,x.grid_1[row],x.grid_6[row],x.grid_3[row],x.grid_2[row],x.grid_1[row],x.grid_2[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],x.grid_3[row],
}
x.grid_1 <- as.numeric(stan_dat$total_puts_American$forward_price_scaled[test_start:test_end])</pre>
x.grid_2 <- as.numeric(stan_dat$total_puts_American$strike_price_scaled[test_start:test_end])</pre>
x.grid_3 <- as.numeric(stan_dat$total_puts_American$impl_volatility[test_start:test_end])</pre>
x.grid_4 <- as.numeric(stan_dat$total_puts_American$time_to_exp[test_start:test_end])</pre>
x.grid_5 <- as.numeric(stan_dat$total_puts_American$dividend[test_start:test_end])</pre>
x.grid_6 <- as.numeric(stan_dat$total_puts_American$interest_rate[test_start:test_end])</pre>
x2 <- cbind(x.grid_1,x.grid_2,x.grid_3,x.grid_4,x.grid_5,x.grid_6)</pre>
1-2: Predictions
post_data_SGP_American <- list(theta=c(post_mean_theta_1_SGP,post_mean_theta_2_SGP,post_mean_theta_3_SG
# post_data
pred_gp_SGP <- stan(file="Predictive GP_6dimension_withBS.stan", data=post_data_SGP_American,iter=200,</pre>
## DIAGNOSTIC(S) FROM PARSER:
## Info: Comments beginning with # are deprecated. Please use // in place of # for line comments.
## Info: Comments beginning with # are deprecated. Please use // in place of # for line comments.
##
## SAMPLING FOR MODEL 'Predictive GP_6dimension_withBS' NOW (CHAIN 1).
## Chain 1: Iteration: 1 / 200 [ 0%]
                                                                                                              (Sampling)
## Chain 1: Iteration: 100 / 200 [ 50%]
                                                                                                              (Sampling)
## Chain 1: Iteration: 200 / 200 [100%] (Sampling)
## Chain 1:
```

```
## Chain 1: Elapsed Time: O seconds (Warm-up)
## Chain 1:
                           29.59 seconds (Sampling)
## Chain 1:
                           29.59 seconds (Total)
## Chain 1:
##Part2: Bdrycov Gaussian Process
2-1: Fitting
# Fitting GP model for Bdrycov
stan_dat <- read_rdump('Financial_Data_Put_American.R')</pre>
## Parsed with column specification:
## cols(
##
     .default = col double(),
##
     date = col_character(),
##
     symbol = col_character(),
##
     exdate = col_character(),
##
     cp_flag = col_character(),
##
    ticker = col_character(),
##
     exercise_style = col_character()
## )
## See spec(...) for full column specifications.
fit_gp_Bdrycov_American <- stan(file="gp-fit-6dimension_withBS_Bdrycov.stan", data=stan_dat,
               iter=100, chains=1);
##
## SAMPLING FOR MODEL 'gp-fit-6dimension_withBS_Bdrycov' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0.416 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would take 4160 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: WARNING: There aren't enough warmup iterations to fit the
## Chain 1:
                     three stages of adaptation as currently configured.
## Chain 1:
                     Reducing each adaptation stage to 15%/75%/10% of
## Chain 1:
                     the given number of warmup iterations:
## Chain 1:
                      init_buffer = 7
## Chain 1:
                       adapt_window = 38
## Chain 1:
                       term_buffer = 5
## Chain 1:
## Chain 1: Iteration: 1 / 100 [ 1%]
                                         (Warmup)
## Chain 1: Iteration: 10 / 100 [ 10%]
                                         (Warmup)
## Chain 1: Iteration: 20 / 100 [ 20%]
                                         (Warmup)
## Chain 1: Iteration: 30 / 100 [ 30%]
                                         (Warmup)
## Chain 1: Iteration: 40 / 100 [ 40%]
                                         (Warmup)
## Chain 1: Iteration: 50 / 100 [ 50%]
                                         (Warmup)
## Chain 1: Iteration: 51 / 100 [ 51%]
                                         (Sampling)
## Chain 1: Iteration: 60 / 100 [ 60%]
                                         (Sampling)
## Chain 1: Iteration: 70 / 100 [ 70%]
                                         (Sampling)
```

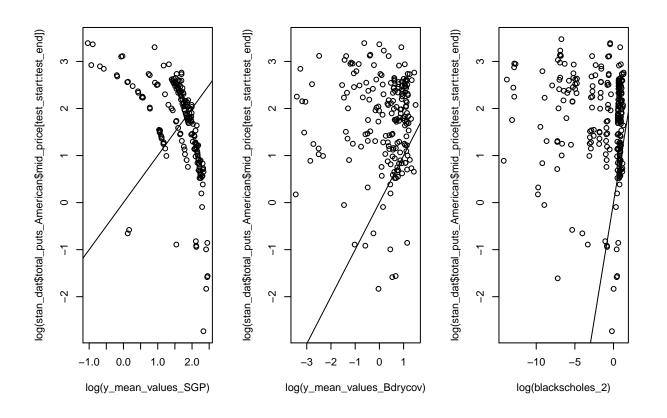
```
## Chain 1: Iteration: 90 / 100 [ 90%]
                                         (Sampling)
## Chain 1: Iteration: 100 / 100 [100%]
                                          (Sampling)
## Chain 1:
## Chain 1: Elapsed Time: 385.753 seconds (Warm-up)
## Chain 1:
                           428.585 seconds (Sampling)
## Chain 1:
                           814.338 seconds (Total)
## Chain 1:
print(fit_gp_Bdrycov_American, pars = c('theta', 'sigma2', 'gamma2'))
## Inference for Stan model: gp-fit-6dimension_withBS_Bdrycov.
## 1 chains, each with iter=100; warmup=50; thin=1;
## post-warmup draws per chain=50, total post-warmup draws=50.
##
##
             mean se mean
                             sd 2.5% 25%
                                             50%
                                                    75% 97.5% n eff Rhat
## theta[1] 1.33
                     0.11 0.67 0.59 0.83 1.13
                                                   1.63
                                                           3.03
                                                                   39 0.98
## theta[2] 1.25
                     0.13 0.73 0.55 0.80 1.05
                                                   1.33
                                                           3.28
                                                                   29 0.99
## theta[3] 1.08
                     0.05 0.50 0.50 0.75 0.97
                                                   1.24
                                                           2.44
                                                                   85 0.98
## theta[4] 1.24
                     0.08 0.59 0.55 0.84 1.16
                                                   1.55
                                                           2.39
                                                                   56 0.98
## theta[5] 1.46
                     0.20 0.93 0.50 0.82 1.14
                                                   1.73
                                                           3.46
                                                                   22 0.98
## theta[6] 1.39
                     0.16 0.80 0.58 0.75 1.15
                                                   1.78
                                                           3.41
                                                                   25 1.00
            63.59
                    19.23 57.43 0.01 2.59 46.53 122.11 152.56
                                                                   9 1.00
## sigma2
                    20.37 59.32 0.30 6.14 81.88 129.62 158.79
## gamma2
            75.14
                                                                    8 1.02
##
## Samples were drawn using NUTS(diag_e) at Fri Mar 27 22:15:26 2020.
## For each parameter, n_eff is a crude measure of effective sample size,
## and Rhat is the potential scale reduction factor on split chains (at
## convergence, Rhat=1).
sum_gp_Bdrycov_American <- extract(fit_gp_Bdrycov_American,permuted=FALSE)</pre>
# saveRDS(fit_gp,file ="fit_gp_vol50_within50spot_7to19days")
# Predicting from GP model - 2 dimensional case
post_mean_theta_1_Bdrycov <- mean(sum_gp_Bdrycov_American[,1,1]) #theta</pre>
post_mean_theta_2_Bdrycov <- mean(sum_gp_Bdrycov_American[,1,2]) #theta</pre>
post_mean_theta_3_Bdrycov <- mean(sum_gp_Bdrycov_American[,1,3]) #theta</pre>
post_mean_theta_4_Bdrycov <- mean(sum_gp_Bdrycov_American[,1,4]) #theta</pre>
post_mean_theta_5_Bdrycov <- mean(sum_gp_Bdrycov_American[,1,5]) #theta</pre>
post mean theta 6 Bdrycov <- mean(sum gp Bdrycov American[,1,6]) #theta
post_mean_sigma2_Bdrycov <- mean(sum_gp_Bdrycov_American[,1,7]) #sigma2</pre>
post_mean_gamma2_Bdrycov <- mean(sum_gp_Bdrycov_American[,1,8]) #gamma2</pre>
post_mean_mu_Bdrycov <- stan_dat$blackscholes</pre>
 \# x2 \leftarrow as.numeric(unlist(spx\_spy\_2019\_06\_30\_put\_2017\_06\_500rows\_test['strike\_price'])) 
# x2<- cbind(spy_2013_01_01_2013_01_31_put$strike_price[201:300],spy_2013_01_01_2013_01_31_put$impl_vol
\# x2 \leftarrow seq(from=-2, to=2, by=0.01)
\# x2 \leftarrow cbind(seq(from=0, to=1, by=0.01), seq(from=0, to=1, by=0.01))
```

(Sampling)

Chain 1: Iteration: 80 / 100 [80%]

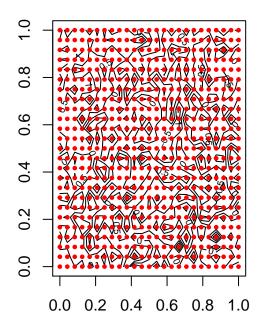
```
\# X.grid \leftarrow expand.grid(x1 = x.grid_1, x2 = x.grid_2)
post_data_Bdrycov_American <- list(theta=c(post_mean_theta_1_Bdrycov,post_mean_theta_2_Bdrycov,post_mean_</pre>
# post_data
pred_gp_Bdrycov <- stan(file="Predictive GP_6dimension_withBS_Bdrycov.stan", data=post_data_Bdrycov_Ame
## DIAGNOSTIC(S) FROM PARSER:
## Info: Comments beginning with # are deprecated. Please use // in place of # for line comments.
## Info: Comments beginning with # are deprecated. Please use // in place of # for line comments.
##
##
## SAMPLING FOR MODEL 'Predictive GP_6dimension_withBS_Bdrycov' NOW (CHAIN 1).
## Chain 1: Iteration: 1 / 200 [ 0%] (Sampling)
## Chain 1: Iteration: 100 / 200 [ 50%] (Sampling)
## Chain 1: Iteration: 200 / 200 [100%] (Sampling)
## Chain 1:
## Chain 1: Elapsed Time: O seconds (Warm-up)
                            60.786 seconds (Sampling)
## Chain 1:
## Chain 1:
                            60.786 seconds (Total)
## Chain 1:
##Part 3 Predictions Versus Truth
3-1: Computing Means Standard GP
#Computing Mean
y_predict_values_SGP <- extract(pred_gp_SGP,permuted=FALSE)</pre>
y_mean_values_SGP <- c(colMeans(y_predict_values_SGP))</pre>
y_mean_values_SGP <- y_mean_values_SGP[1:(length(y_mean_values_SGP)-1)]</pre>
#Computing Standard Deviation
pred_gp_summary_SGP <- summary(pred_gp_SGP, sd=c("sd"))$summary</pre>
pred_gp_sd_SGP <- pred_gp_summary_SGP[, c("sd")]</pre>
y_sd_values_SGP <- pred_gp_sd_SGP[1:(length(pred_gp_sd_SGP)-1)]</pre>
3-2: Computing Means Bdrycov
#Computing Mean
y_predict_values_Bdrycov <- extract(pred_gp_Bdrycov,permuted=FALSE)</pre>
y_mean_values_Bdrycov <- c(colMeans(y_predict_values_Bdrycov))</pre>
y_mean_values_Bdrycov <- y_mean_values_Bdrycov[1:(length(y_mean_values_Bdrycov)-1)]
#Computing Standard Deviation
pred_gp_summary_Bdrycov <- summary(pred_gp_Bdrycov, sd=c("sd"))$summary</pre>
pred_gp_sd_Bdrycov <- pred_gp_summary_Bdrycov[, c("sd")]</pre>
y_sd_values_Bdrycov <- pred_gp_sd_Bdrycov[1:(length(pred_gp_sd_Bdrycov)-1)]</pre>
3-3: Plotting Predicted Values against Truth
```

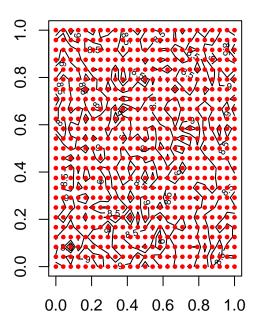
```
## Warning in log(y_mean_values_SGP): NaNs produced
## Warning in log(y_mean_values_SGP): NaNs produced
## Warning in log(y_mean_values_SGP): NaNs produced
abline(0,1)
#Plotting BDrycov
plot(log(y_mean_values_Bdrycov),log(stan_dat$total_puts_American$mid_price[test_start:test_end]), xlim
## Warning in log(y_mean_values_Bdrycov): NaNs produced
abline(0,1)
#Plotting Blackscholes
plot(log(blackscholes_2),log(stan_dat$total_puts_American$mid_price[test_start:test_end]), xlim = c(min abline(0,1))
```



```
#MSE
library('MLmetrics')
## Attaching package: 'MLmetrics'
## The following object is masked from 'package:base':
##
##
       Recall
MSE(y_mean_values_SGP,stan_dat$total_puts_American$mid_price[test_start:test_end])
## [1] 110.5443
MSE(y_mean_values_Bdrycov,stan_dat$total_puts_American$mid_price[test_start:test_end])
## [1] 92.0102
MSE(blackscholes_2,stan_dat$total_puts_American$mid_price[test_start:test_end])
## [1] 92.78114
##Part 4 Visualizations
4-1: Contour Plots of Forward Price & Strike Price
x.grid_1_cont <- as.numeric(stan_dat$total_puts_American$forward_price_scaled[test_start:test_end])</pre>
x.grid_2_cont <- as.numeric(stan_dat$total_puts_American$strike_price_scaled[test_start:test_end])</pre>
dim1 \leftarrow seq(0.000000001, 1.000000001, length.out = 25)
dim2 \leftarrow seq(0.000000001, 1.000000001, length.out = 25)
X.grid <- expand.grid(x1 = dim1, x2 = dim2)</pre>
x.grid_3_cont <- as.numeric(rep(mean(stan_dat$total_puts_American$impl_volatility[test_start:test_end])</pre>
x.grid_4_cont <- as.numeric(rep(mean(stan_dat$total_puts_American$time_to_exp[test_start:test_end])),nr
x.grid_5_cont <- as.numeric(rep(mean(stan_dat$total_puts_American$dividend_yield[test_start:test_end]))</pre>
x.grid_6_cont <- as.numeric(rep(mean(stan_dat$total_puts_American$interest_rate[test_start:test_end])),</pre>
x2_cont <- cbind(X.grid,x.grid_3_cont,x.grid_4_cont,x.grid_5_cont,x.grid_6_cont)</pre>
blackscholes_2_cont <- rep(NA,length(x2_cont[,1]))
for (row in 1:nrow(data.frame(x2_cont))){
  blackscholes_2_cont[row] <- as.numeric(blackscholes(-1,S0=x2_cont[row,1],K=x2_cont[row,2],r=x2_cont[r
post_data_cont <- list(theta=c(post_mean_theta_1_Bdrycov,post_mean_theta_2_Bdrycov,post_mean_theta_3_Bd
# post_data
pred_gp_cont <- stan(file="Predictive GP_6dimension_withBS_Bdrycov.stan", data=post_data_cont,iter=200,
```

```
## DIAGNOSTIC(S) FROM PARSER:
## Info: Comments beginning with # are deprecated. Please use // in place of # for line comments.
## Info: Comments beginning with # are deprecated. Please use // in place of # for line comments.
##
## SAMPLING FOR MODEL 'Predictive GP 6dimension withBS Bdrycov' NOW (CHAIN 1).
## Chain 1: Iteration: 1 / 200 [ 0%]
                                          (Sampling)
## Chain 1: Iteration: 100 / 200 [ 50%]
                                           (Sampling)
## Chain 1: Iteration: 200 / 200 [100%]
                                          (Sampling)
## Chain 1:
## Chain 1: Elapsed Time: O seconds (Warm-up)
## Chain 1:
                            203.437 seconds (Sampling)
## Chain 1:
                            203.437 seconds (Total)
## Chain 1:
#Computing Mean
y_predict_values_cont <- extract(pred_gp_cont,permuted=FALSE)</pre>
y_mean_values_cont <- c(colMeans(y_predict_values_cont))</pre>
y_mean_values_cont <- y_mean_values_cont[1:(length(y_mean_values_cont)-1)]</pre>
#Computing Standard Deviation
pred_gp_summary_cont <- summary(pred_gp_cont, sd=c("sd"))$summary</pre>
pred_gp_sd_cont <- pred_gp_summary_cont[, c("sd")]</pre>
y_sd_values_cont <- pred_gp_sd_cont[1:(length(pred_gp_sd_cont)-1)]</pre>
par(mfrow = c(1, 2))
#Contour for Predictions aka mean values of predicitons
\#x1\_grid\_cont \leftarrow seq(from=min(x.grid\_1\_cont), to=max(x.grid\_1\_cont), length.out=length(x.grid\_1\_cont))
\# x2\_grid\_cont \leftarrow seq(from=min(x.grid\_2\_cont), to=max(x.grid\_2\_cont), length.out=length(x.grid\_2\_cont))
contour(dim1, dim2, matrix(y_mean_values_cont, length(dim1), length(dim2)))
points(x2_cont[,1], x2_cont[,2], pch = 19, cex = 0.5, col = "red")
#Contour of Variance
contour(dim1, dim2, matrix(y_sd_values_cont, length(dim1), length(dim2)))
points(x2_cont[,1], x2_cont[,2], pch = 19, cex = 0.5, col = "red")
```

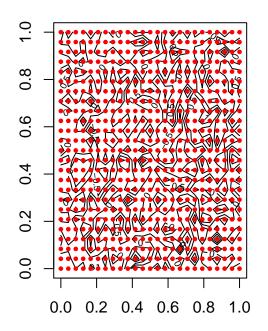


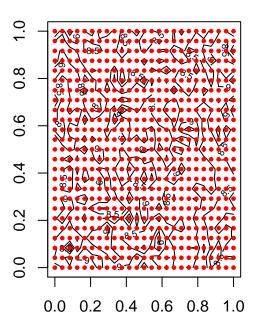


4-2: Contour Plots of Implied VOlatility & Time to Expiration

```
x.grid_1_cont <- as.numeric(stan_dat$total_puts_American$impl_volatility[test_start:test_end])</pre>
x.grid_2_cont <- as.numeric(stan_dat$total_puts_American$time_to_exp[test_start:test_end])</pre>
dim1 <- seq(0.000000001,1.000000001,length.out = 25)</pre>
dim2 \leftarrow seq(0.000000001, 1.000000001, length.out = 25)
X.grid <- expand.grid(x1 = dim1, x2 = dim2)</pre>
x.grid_3_cont <- as.numeric(rep(mean(stan_dat$total_puts_American$forward_price_scaled[test_start:test_
x.grid_4_cont <- as.numeric(rep(mean(stan_dat$total_puts_American$strike_price_scaled[test_start:test_e:
x.grid_5_cont <- as.numeric(rep(mean(stan_dat$total_puts_American$dividend_yield[test_start:test_end]))</pre>
x.grid_6_cont <- as.numeric(rep(mean(stan_dat$total_puts_American$interest_rate[test_start:test_end])),</pre>
x2_cont <- cbind(X.grid,x.grid_3_cont,x.grid_4_cont,x.grid_5_cont,x.grid_6_cont)</pre>
blackscholes_2_cont <- rep(NA,length(x2_cont[,1]))</pre>
for (row in 1:nrow(data.frame(x2_cont))){
  blackscholes_2_cont[row] <- as.numeric(blackscholes(-1,S0=x2_cont[row,3],K=x2_cont[row,4],r=x2_cont[r
}
post_data_cont <- list(theta=c(post_mean_theta_1_Bdrycov,post_mean_theta_2_Bdrycov,post_mean_theta_3_Bd
\# post_data
pred_gp_cont <- stan(file="Predictive GP_6dimension_withBS_Bdrycov.stan", data=post_data_cont,iter=200,
```

```
## DIAGNOSTIC(S) FROM PARSER:
## Info: Comments beginning with # are deprecated. Please use // in place of # for line comments.
## Info: Comments beginning with # are deprecated. Please use // in place of # for line comments.
##
## SAMPLING FOR MODEL 'Predictive GP 6dimension withBS Bdrycov' NOW (CHAIN 1).
## Chain 1: Iteration: 1 / 200 [ 0%]
                                          (Sampling)
## Chain 1: Iteration: 100 / 200 [ 50%]
                                           (Sampling)
## Chain 1: Iteration: 200 / 200 [100%]
                                          (Sampling)
## Chain 1:
## Chain 1: Elapsed Time: O seconds (Warm-up)
## Chain 1:
                            173.783 seconds (Sampling)
## Chain 1:
                            173.783 seconds (Total)
## Chain 1:
#Computing Mean
y_predict_values_cont <- extract(pred_gp_cont,permuted=FALSE)</pre>
y_mean_values_cont <- c(colMeans(y_predict_values_cont))</pre>
y_mean_values_cont <- y_mean_values_cont[1:(length(y_mean_values_cont)-1)]</pre>
#Computing Standard Deviation
pred_gp_summary_cont <- summary(pred_gp_cont, sd=c("sd"))$summary</pre>
pred_gp_sd_cont <- pred_gp_summary_cont[, c("sd")]</pre>
y_sd_values_cont <- pred_gp_sd_cont[1:(length(pred_gp_sd_cont)-1)]</pre>
par(mfrow = c(1, 2))
#Contour for Predictions aka mean values of predicitons
\#x1\_grid\_cont \leftarrow seq(from=min(x.grid\_1\_cont), to=max(x.grid\_1\_cont), length.out=length(x.grid\_1\_cont))
\# x2\_grid\_cont \leftarrow seq(from=min(x.grid\_2\_cont), to=max(x.grid\_2\_cont), length.out=length(x.grid\_2\_cont))
contour(dim1, dim2, matrix(y_mean_values_cont, length(dim1), length(dim2)))
points(x2_cont[,1], x2_cont[,2], pch = 19, cex = 0.5, col = "red")
#Contour of Variance
contour(dim1, dim2, matrix(y_sd_values_cont, length(dim1), length(dim2)))
points(x2_cont[,1], x2_cont[,2], pch = 19, cex = 0.5, col = "red")
```

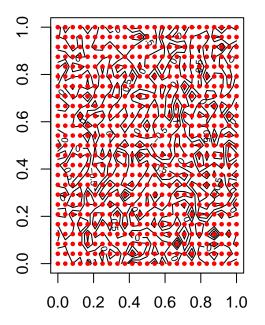


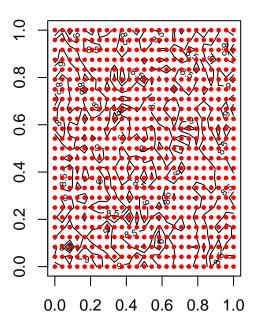


4-3: Contour Plots of Interest Rate & Time to Expiration

```
x.grid_1_cont <- as.numeric(stan_dat$total_puts_American$interest_rate[test_start:test_end])</pre>
x.grid_2_cont <- as.numeric(stan_dat$total_puts_American$time_to_exp[test_start:test_end])</pre>
dim1 <- seq(0.000000001,1.000000001,length.out = 25)</pre>
dim2 \leftarrow seq(0.000000001, 1.000000001, length.out = 25)
X.grid <- expand.grid(x1 = dim1, x2 = dim2)</pre>
x.grid_3_cont <- as.numeric(rep(mean(stan_dat$total_puts_American$forward_price_scaled[test_start:test_
x.grid_4_cont <- as.numeric(rep(mean(stan_dat$total_puts_American$strike_price_scaled[test_start:test_e:
x.grid_5_cont <- as.numeric(rep(mean(stan_dat$total_puts_American$impl_volatility[test_start:test_end])</pre>
x.grid_6_cont <- as.numeric(rep(mean(stan_dat$total_puts_American$dividend_yield[test_start:test_end]))</pre>
x2_cont <- cbind(X.grid,x.grid_3_cont,x.grid_4_cont,x.grid_5_cont,x.grid_6_cont)</pre>
blackscholes_2_cont <- rep(NA,length(x2_cont[,1]))</pre>
for (row in 1:nrow(data.frame(x2_cont))){
  blackscholes_2_cont[row] <- as.numeric(blackscholes(-1,S0=x2_cont[row,3],K=x2_cont[row,4],r=x2_cont[r
}
post_data_cont <- list(theta=c(post_mean_theta_1_Bdrycov,post_mean_theta_2_Bdrycov,post_mean_theta_3_Bd
\# post_data
pred_gp_cont <- stan(file="Predictive GP_6dimension_withBS_Bdrycov.stan", data=post_data_cont,iter=200,
```

```
## DIAGNOSTIC(S) FROM PARSER:
## Info: Comments beginning with # are deprecated. Please use // in place of # for line comments.
## Info: Comments beginning with # are deprecated. Please use // in place of # for line comments.
##
## SAMPLING FOR MODEL 'Predictive GP 6dimension withBS Bdrycov' NOW (CHAIN 1).
## Chain 1: Iteration: 1 / 200 [ 0%]
                                          (Sampling)
## Chain 1: Iteration: 100 / 200 [ 50%]
                                           (Sampling)
## Chain 1: Iteration: 200 / 200 [100%]
                                          (Sampling)
## Chain 1:
## Chain 1: Elapsed Time: O seconds (Warm-up)
## Chain 1:
                            173.928 seconds (Sampling)
## Chain 1:
                            173.928 seconds (Total)
## Chain 1:
#Computing Mean
y_predict_values_cont <- extract(pred_gp_cont,permuted=FALSE)</pre>
y_mean_values_cont <- c(colMeans(y_predict_values_cont))</pre>
y_mean_values_cont <- y_mean_values_cont[1:(length(y_mean_values_cont)-1)]</pre>
#Computing Standard Deviation
pred_gp_summary_cont <- summary(pred_gp_cont, sd=c("sd"))$summary</pre>
pred_gp_sd_cont <- pred_gp_summary_cont[, c("sd")]</pre>
y_sd_values_cont <- pred_gp_sd_cont[1:(length(pred_gp_sd_cont)-1)]</pre>
par(mfrow = c(1, 2))
#Contour for Predictions aka mean values of predicitons
\#x1\_grid\_cont \leftarrow seq(from=min(x.grid\_1\_cont), to=max(x.grid\_1\_cont), length.out=length(x.grid\_1\_cont))
\# x2\_grid\_cont \leftarrow seq(from=min(x.grid\_2\_cont), to=max(x.grid\_2\_cont), length.out=length(x.grid\_2\_cont))
contour(dim1, dim2, matrix(y_mean_values_cont, length(dim1), length(dim2)))
points(x2_cont[,1], x2_cont[,2], pch = 19, cex = 0.5, col = "red")
#Contour of Variance
contour(dim1, dim2, matrix(y_sd_values_cont, length(dim1), length(dim2)))
points(x2_cont[,1], x2_cont[,2], pch = 19, cex = 0.5, col = "red")
```





##Part 5: Improving the model by incorporating discrepancy

5-1: Computing Predicted European Option Prices

```
library(rstan)
source("gp.utility.R")
# Fitting GP model
stan_dat_European <- read_rdump('Financial_Data_Put_European.R')</pre>
## Parsed with column specification:
## cols(
##
     .default = col_double(),
     date = col_character(),
##
     symbol = col_character(),
##
##
     exdate = col_character(),
     cp_flag = col_character(),
##
     ticker = col_character(),
##
     exercise_style = col_character()
##
## )
## See spec(...) for full column specifications.
fit_gp_SGP_European <- stan(file="gp-fit-6dimension_withBS.stan", data=stan_dat_European,</pre>
               iter=100, chains=1);
```

```
## DIAGNOSTIC(S) FROM PARSER:
## Info: Comments beginning with # are deprecated. Please use // in place of # for line comments.
##
##
## SAMPLING FOR MODEL 'gp-fit-6dimension_withBS' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0.015 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would take 150 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: WARNING: There aren't enough warmup iterations to fit the
## Chain 1:
                     three stages of adaptation as currently configured.
## Chain 1:
                     Reducing each adaptation stage to 15%/75%/10% of
## Chain 1:
                     the given number of warmup iterations:
## Chain 1:
                       init_buffer = 7
## Chain 1:
                       adapt_window = 38
## Chain 1:
                       term_buffer = 5
## Chain 1:
## Chain 1: Iteration: 1 / 100 [ 1%]
                                         (Warmup)
## Chain 1: Iteration: 10 / 100 [ 10%]
                                         (Warmup)
## Chain 1: Iteration: 20 / 100 [ 20%]
                                         (Warmup)
## Chain 1: Iteration: 30 / 100 [ 30%]
                                         (Warmup)
## Chain 1: Iteration: 40 / 100 [ 40%]
                                         (Warmup)
## Chain 1: Iteration: 50 / 100 [ 50%]
                                         (Warmup)
## Chain 1: Iteration: 51 / 100 [ 51%]
                                         (Sampling)
## Chain 1: Iteration: 60 / 100 [ 60%]
                                         (Sampling)
## Chain 1: Iteration: 70 / 100 [ 70%]
                                         (Sampling)
## Chain 1: Iteration: 80 / 100 [ 80%]
                                         (Sampling)
## Chain 1: Iteration: 90 / 100 [ 90%]
                                         (Sampling)
## Chain 1: Iteration: 100 / 100 [100%]
                                          (Sampling)
## Chain 1:
## Chain 1: Elapsed Time: 15.119 seconds (Warm-up)
                           12.515 seconds (Sampling)
## Chain 1:
## Chain 1:
                           27.634 seconds (Total)
## Chain 1:
print(fit_gp_SGP_European, pars = c('theta','sigma2','gamma2'))
## Inference for Stan model: gp-fit-6dimension_withBS.
## 1 chains, each with iter=100; warmup=50; thin=1;
## post-warmup draws per chain=50, total post-warmup draws=50.
##
##
                                               2.5%
                                                           25%
                                                                     50%
                 mean se_mean
                                       sd
## theta[1]
                 0.18
                           0.00
                                     0.03
                                               0.14
                                                          0.16
                                                                    0.17
## theta[2]
                 2.21
                           0.06
                                     0.48
                                               1.53
                                                          1.87
                                                                    2.10
## theta[3]
                 8.41
                          0.35
                                     1.99
                                               5.33
                                                          7.13
                                                                    8.25
## theta[4]
                 0.22
                          0.00
                                     0.03
                                               0.18
                                                          0.20
                                                                    0.22
## theta[5]
                           0.11
                                     0.62
                                               0.46
                                                          0.70
                                                                    0.91
                 1.12
## theta[6]
                                               0.83
                 1.76
                          0.14
                                     0.71
                                                          1.14
                                                                    1.65
## sigma2
                 0.00
                           0.00
                                     0.00
                                               0.00
                                                          0.00
                                                                    0.00
## gamma2
            266431.22 14712.74 104936.79 127741.62 205796.51 254846.75
                          97.5% n_eff Rhat
                  75%
                                    85 0.98
## theta[1]
                 0.19
                           0.23
```

```
## theta[2]
                  2.37
                            3.23
                                     61 0.99
## theta[3]
                  9.48
                           12.71
                                     31 1.02
## theta[4]
                  0.23
                            0.27
                                     85 0.98
## theta[5]
                  1.44
                            2.15
                                     33 1.00
## theta[6]
                  2.25
                            3.10
                                     25 0.99
                  0.00
                            0.00
                                     85 0.98
## sigma2
            303771.02 461181.51
                                     51 0.98
## gamma2
##
## Samples were drawn using NUTS(diag_e) at Fri Mar 27 22:27:44 2020.
## For each parameter, n_eff is a crude measure of effective sample size,
## and Rhat is the potential scale reduction factor on split chains (at
## convergence, Rhat=1).
sum_gp_SGP_European <- extract(fit_gp_SGP_European,permuted=FALSE)</pre>
# Predicting from GP model
post_mean_theta_1_SGP <- mean(sum_gp_SGP_European[,1,1]) #theta</pre>
post_mean_theta_2_SGP <- mean(sum_gp_SGP_European[,1,2]) #theta</pre>
post_mean_theta_3_SGP <- mean(sum_gp_SGP_European[,1,3]) #theta</pre>
post_mean_theta_4_SGP <- mean(sum_gp_SGP_European[,1,4]) #theta</pre>
post_mean_theta_5_SGP <- mean(sum_gp_SGP_European[,1,5]) #theta</pre>
post_mean_theta_6_SGP <- mean(sum_gp_SGP_European[,1,6]) #theta</pre>
post_mean_sigma2_SGP <- mean(sum_gp_SGP_European[,1,7]) #siqma2</pre>
post_mean_gamma2_SGP <- mean(sum_gp_SGP_European[,1,8]) #gamma2</pre>
post_mean_mu_SGP <- stan_dat_European$blackscholes</pre>
x.grid_1 <- as.numeric(stan_dat$total_puts_American$forward_price[test_start:test_end])</pre>
x.grid_2 <- as.numeric(stan_dat$total_puts_American$strike_price[test_start:test_end])</pre>
x.grid_3 <- as.numeric(stan_dat$total_puts_American$impl_volatility[test_start:test_end])</pre>
x.grid_4 <- as.numeric(stan_dat$total_puts_American$time_to_exp[test_start:test_end]*250)</pre>
x.grid_5 <- as.numeric(stan_dat$total_puts_American$dividend[test_start:test_end])</pre>
x.grid_6 <- as.numeric(stan_dat$total_puts_American$interest_rate[test_start:test_end])</pre>
x2 <- cbind(x.grid_1,x.grid_2,x.grid_3,x.grid_4,x.grid_5,x.grid_6)</pre>
library('qrmtools')
library('ragtop')
blackscholes_2 <- rep(NA,length(x2[,1]))</pre>
for (row in 1:nrow(data.frame(x2))){
  blackscholes_2[row] <- as.numeric(blackscholes(-1,S0=x.grid_1[row],K=x.grid_2[row],r=x.grid_6[row],t=
  \# blackscholes_2[row] <- Black_Scholes(0,x.grid_1[row],x.grid_6[row],x.grid_3[row],x.grid_2[row],x.gr
}
x.grid_1 <- as.numeric(stan_dat$total_puts_American$forward_price_scaled[test_start:test_end])</pre>
x.grid_2 <- as.numeric(stan_dat$total_puts_American$strike_price_scaled[test_start:test_end])</pre>
x.grid_3 <- as.numeric(stan_dat$total_puts_American$impl_volatility[test_start:test_end])</pre>
x.grid_4 <- as.numeric(stan_dat$total_puts_American$time_to_exp[test_start:test_end])</pre>
x.grid_5 <- as.numeric(stan_dat$total_puts_American$dividend[test_start:test_end])</pre>
x.grid_6 <- as.numeric(stan_dat$total_puts_American$interest_rate[test_start:test_end])</pre>
x2 <- cbind(x.grid_1,x.grid_2,x.grid_3,x.grid_4,x.grid_5,x.grid_6)</pre>
\# X.grid \leftarrow expand.grid(x1 = x.grid_1, x2 = x.grid_2)
post_data_Bdrycov_American_disc <- list(theta=c(post_mean_theta_1_SGP,post_mean_theta_2_SGP,post_mean_t.
```

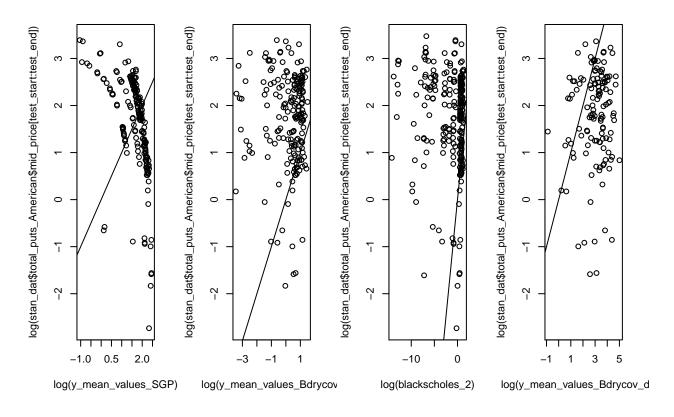
```
# post_data
pred gp Bdrycov disc <- stan(file="Predictive GP 6dimension withBS Bdrycov.stan", data=post data Bdryco
## DIAGNOSTIC(S) FROM PARSER:
## Info: Comments beginning with # are deprecated. Please use // in place of # for line comments.
## Info: Comments beginning with # are deprecated. Please use // in place of # for line comments.
##
##
## SAMPLING FOR MODEL 'Predictive GP_6dimension_withBS_Bdrycov' NOW (CHAIN 1).
## Chain 1: Iteration: 1 / 200 [ 0%]
                                         (Sampling)
                                          (Sampling)
## Chain 1: Iteration: 100 / 200 [ 50%]
## Chain 1: Iteration: 200 / 200 [100%]
                                         (Sampling)
## Chain 1:
## Chain 1: Elapsed Time: O seconds (Warm-up)
## Chain 1:
                           25.555 seconds (Sampling)
## Chain 1:
                           25.555 seconds (Total)
## Chain 1:
#Computing Mean
y_predict_values_Bdrycov_disc <- extract(pred_gp_Bdrycov_disc,permuted=FALSE)</pre>
y_mean_values_Bdrycov_disc <- c(colMeans(y_predict_values_Bdrycov_disc))</pre>
y_mean_values_Bdrycov_disc <- y_mean_values_Bdrycov_disc[1:(length(y_mean_values_Bdrycov_disc)-1)]
#Computing Standard Deviation
pred_gp_summary_Bdrycov_disc <- summary(pred_gp_Bdrycov_disc, sd=c("sd"))$summary</pre>
pred gp sd Bdrycov disc <- pred gp summary Bdrycov disc[, c("sd")]</pre>
y_sd_values_Bdrycov_disc <- pred_gp_sd_Bdrycov_disc[1:(length(pred_gp_sd_Bdrycov_disc)-1)]
3-3: Plotting Predicted Values against Truth
par(mfrow=c(1,4))
#Plotting Standard GP
plot(log(y mean values SGP),log(stan dat$total puts American$mid price[test start:test end]),xlim = c(m
## Warning in log(y_mean_values_SGP): NaNs produced
## Warning in log(y_mean_values_SGP): NaNs produced
## Warning in log(y_mean_values_SGP): NaNs produced
abline(0,1)
#Plotting BDrycov
plot(log(y_mean_values_Bdrycov),log(stan_dat$total_puts_American$mid_price[test_start:test_end]), xlim =
## Warning in log(y_mean_values_Bdrycov): NaNs produced
## Warning in log(y_mean_values_Bdrycov): NaNs produced
## Warning in log(y_mean_values_Bdrycov): NaNs produced
```

```
abline(0,1)
#Plotting Blackscholes
plot(log(blackscholes_2),log(stan_dat$total_puts_American$mid_price[test_start:test_end]), xlim = c(min
abline(0,1)

#Plotting Discrepancy Model
plot(log(y_mean_values_Bdrycov_disc),log(stan_dat$total_puts_American$mid_price[test_start:test_end]), :

## Warning in log(y_mean_values_Bdrycov_disc): NaNs produced

## Warning in log(y_mean_values_Bdrycov_disc): NaNs produced
```



```
#MSE
library('MLmetrics')
MSE(y_mean_values_SGP,stan_dat$total_puts_American$mid_price[test_start:test_end])
```

[1] 110.5443

```
MSE(y_mean_values_Bdrycov,stan_dat$total_puts_American$mid_price[test_start:test_end])
## [1] 92.0102

MSE(blackscholes_2,stan_dat$total_puts_American$mid_price[test_start:test_end])

## [1] 92.78114

MSE(y_mean_values_Bdrycov_disc,stan_dat$total_puts_American$mid_price[test_start:test_end])

## [1] 1556.101
```