Gaussian_Process_Code

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```
##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 0.073 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would take 730 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: Elapsed Time: 47.761 seconds (Warm-up)
## Chain 1:
                            52.859 seconds (Sampling)
## Chain 1:
                            100.62 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% n eff Rhat
                                                                   29 0.98
## theta[1] 2.13
                     0.16  0.88  0.90  1.46  2.00  2.66  3.83
## theta[2] 1.76
                     0.11 0.66 0.82 1.41 1.72 2.02 2.90
                                                                   35 1.00
## theta[3] 3.43
                     0.09 0.87 1.98 2.82 3.37 3.83 5.30
                                                                   85 0.98
## theta[4] 1.67
                     0.03 0.24 1.31 1.49 1.61 1.86 2.11
                                                                   48 1.01
                     0.17 \quad 0.95 \quad 0.50 \quad 1.04 \quad 1.52 \quad 2.10 \quad 4.36
                                                                   33 0.98
## theta[5] 1.71
## theta[6] 0.66
                     0.02 0.17 0.42 0.57 0.62 0.75 1.04
                                                                   84 0.98
## sigma2
             0.00
                     0.00 0.00 0.00 0.00 0.00 0.00 0.00
                                                                   47 0.98
## gamma2
            28.75
                     1.95 12.77 11.75 19.43 24.64 36.24 55.42
                                                                   43 0.99
##
## Samples were drawn using NUTS(diag_e) at Sun Mar 29 18:26:51 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</pre>
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$blackscholes</pre>
test_start <- 323 #06/10
test_end <- 559 #06/14
# test_start <- 560 #06/17
# test_end <- 852 #06/20
x2_bs <- cbind(as.numeric(stan_dat$total_puts_American$forward_price[test_start:test_end]),as.numeric(s</pre>
library('qrmtools')
## Registered S3 method overwritten by 'xts':
     method
```

##

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_bs[,1]))</pre>
for (row in 1:nrow(data.frame(x2_bs))){
  blackscholes_2[row] <- as.numeric(blackscholes(-1,S0=as.numeric(stan_dat$total_puts_American$forward_
}
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_scaled[test_start:test_end])</pre>
x.grid_4 <- as.numeric(stan_dat$total_puts_American$time_to_exp_scaled[test_start:test_end])</pre>
x.grid_5 <- as.numeric(stan_dat$total_puts_American$dividend_yield_scaled[test_start:test_end])</pre>
x.grid_6 <- as.numeric(stan_dat$total_puts_American$interest_rate_scaled[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).
                          1 / 200 [ 0%]
## Chain 1: Iteration:
                                           (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:
                            23.835 seconds (Sampling)
## Chain 1:
                            23.835 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 0.392 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would take 3920 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: 323.78 seconds (Warm-up)
## Chain 1:
                           276.541 seconds (Sampling)
## Chain 1:
                           600.321 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.
##
                           sd 2.5% 25% 50% 75% 97.5% n_eff Rhat
##
            mean se_mean
```

```
## theta[1] 1.10
                                   0.07 0.49 0.59 0.77 0.95 1.16 2.36
                                                                                                        51 0.99
## theta[2] 1.27
                                  0.11 0.64 0.56 0.82 1.15 1.47 2.82
                                                                                                        35 1.00
## theta[3] 1.31 0.10 0.64 0.48 0.79 1.16 1.82 2.56
                                                                                                        41 0.99
41 0.98
                               0.15 0.89 0.45 0.67 0.92 1.51 3.58
## theta[5] 1.28
                                                                                                        34 1.02
## theta[6] 1.19   0.06 0.52 0.54 0.84 1.01 1.41 2.45
                                                                                                       70 1.01
## sigma2
                    2.61
                                   0.81 1.87 0.05 0.64 2.98 4.33 5.02
                                                                                                         5 1.11
                                   0.83 1.90 0.02 0.06 1.64 4.06 4.72
## gamma2
                     1.95
                                                                                                          5 1.13
##
## Samples were drawn using NUTS(diag_e) at Sun Mar 29 18:39:32 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</pre>
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 <- 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_voltoner
\# 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))
2-2: Predictions
\# X.qrid \leftarrow expand.qrid(x1 = x.qrid_1, x2 = x.qrid_2)
post_data_Bdrycov_American <- list(theta=c(post_mean_theta_1_Bdrycov,post_mean_theta_2_Bdrycov,post_mean_theta_2_Bdrycov,post_mean_theta_2_bdrycov,post_mean_theta_2_bdrycov,post_mean_theta_1_Bdrycov,post_mean_theta_2_bdrycov,post_mean_theta_2_bdrycov,post_mean_theta_2_bdrycov,post_mean_theta_2_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,post_mean_theta_3_bdrycov,p
# post_data
pred_gp_Bdrycov <- stan(file="Predictive GP_6dimension_withBS_Bdrycov.stan", data=post_data_Bdrycov_Ame</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_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)
                            53.561 seconds (Sampling)
## Chain 1:
                             53.561 seconds (Total)
## Chain 1:
## 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)
y_mean_values_Bdrycov <- c(colMeans(y_predict_values_Bdrycov))
y_mean_values_Bdrycov <- y_mean_values_Bdrycov[1:(length(y_mean_values_Bdrycov)-1)]

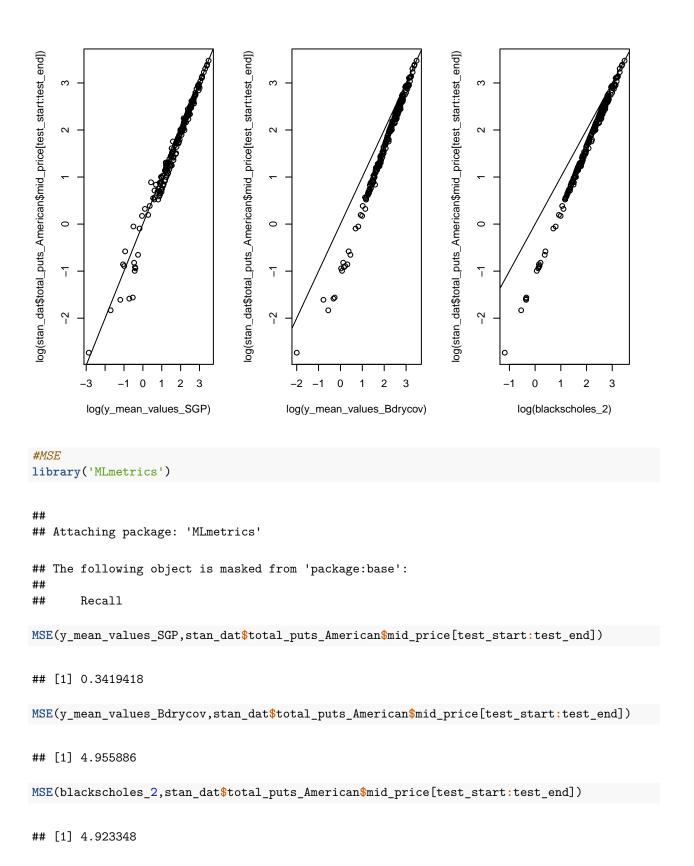
#Computing Standard Deviation
pred_gp_summary_Bdrycov <- summary(pred_gp_Bdrycov, sd=c("sd"))$summary
pred_gp_sd_Bdrycov <- pred_gp_summary_Bdrycov[, c("sd")]
y_sd_values_Bdrycov <- pred_gp_sd_Bdrycov[1:(length(pred_gp_sd_Bdrycov)-1)]</pre>
```

3-3: Plotting Predicted Values against Truth

```
par(mfrow=c(1,3))
#Plotting Standard GP
plot(log(y_mean_values_SGP),log(stan_dat$total_puts_American$mid_price[test_start:test_end]),xlim = c(mabline(0,1)

#Plotting BDrycov
plot(log(y_mean_values_Bdrycov),log(stan_dat$total_puts_American$mid_price[test_start:test_end]), xlim = abline(0,1)

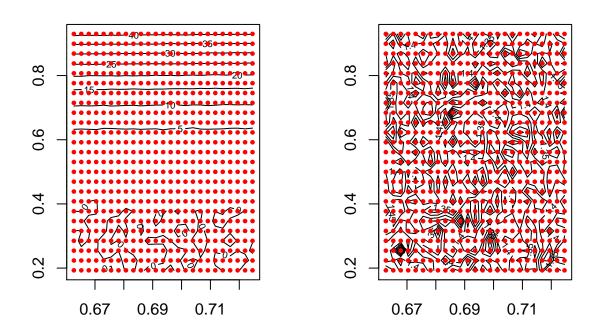
#Plotting Blackscholes
plot(log(blackscholes_2),log(stan_dat$total_puts_American$mid_price[test_start:test_end]), xlim = c(min_abline(0,1))
```



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 <- seq(min(x.grid_1_cont), max(x.grid_1_cont), length.out = 25)</pre>
dim2 <- seq(min(x.grid_2_cont), max(x.grid_2_cont), length.out = 25)</pre>
X.grid <- expand.grid(x1 = dim1, x2 = dim2)</pre>
x.grid_3_cont <- as.numeric(rep(mean(stan_dat$total_puts_American$impl_volatility_scaled[test_start:tes
x.grid_4_cont <- as.numeric(rep(mean(stan_dat$total_puts_American$time_to_exp_scaled[test_start:test_en
x.grid_5_cont <- as.numeric(rep(mean(stan_dat$total_puts_American$dividend_yield_scaled[test_start:test
x.grid_6_cont <- as.numeric(rep(mean(stan_dat$total_puts_American$interest_rate_scaled[test_start:test_
x2_cont <- cbind(X.grid,x.grid_3_cont,x.grid_4_cont,x.grid_5_cont,x.grid_6_cont)</pre>
x.grid_1_cont_bs <- as.numeric(stan_dat$total_puts_American$forward_price[test_start:test_end])</pre>
x.grid_2_cont_bs <- as.numeric(stan_dat$total_puts_American$strike_price[test_start:test_end])
x.grid_3_cont_bs <- as.numeric(rep(mean(stan_dat$total_puts_American$impl_volatility[test_start:test_en
x.grid_4_cont_bs <- as.numeric(rep(mean(stan_dat$total_puts_American$time_to_exp[test_start:test_end]))
x.grid_5_cont_bs <- as.numeric(rep(mean(stan_dat$total_puts_American$dividend_yield[test_start:test_end
x.grid 6 cont bs <- as.numeric(rep(mean(stan dat$total puts American$interest rate[test start:test end]
dim1_bs <- seq(min(x.grid_1_cont_bs), max(x.grid_1_cont_bs), length.out = 25)
dim2_bs <- seq(min(x.grid_2_cont_bs), max(x.grid_2_cont_bs), length.out = 25)
X.grid_bs <- expand.grid(x1 = dim1_bs, x2 = dim2_bs)</pre>
x2_cont_bs <- cbind(X.grid_bs,x.grid_3_cont_bs,x.grid_4_cont_bs,x.grid_5_cont_bs,x.grid_6_cont_bs)
blackscholes_2_cont <- rep(NA,length(x2_cont_bs[,1]))
for (row in 1:nrow(data.frame(x2_cont_bs))){
  blackscholes_2_cont[row] <- as.numeric(blackscholes(-1,S0=x2_cont_bs[row,1],K=x2_cont_bs[row,2],r=x2_
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: 0 seconds (Warm-up)
## Chain 1:
                           150.453 seconds (Sampling)
```

```
## Chain 1:
                            150.453 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
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

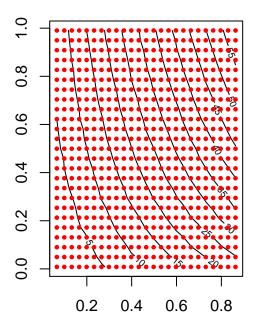
```
x.grid_1_cont <- as.numeric(stan_dat$total_puts_American$impl_volatility_scaled[test_start:test_end])
x.grid_2_cont <- as.numeric(stan_dat$total_puts_American$time_to_exp_scaled[test_start:test_end])</pre>
```

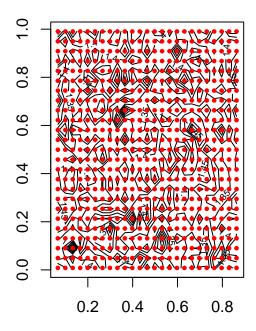
```
dim1 <- seq(min(x.grid_1_cont), max(x.grid_1_cont), length.out = 25)</pre>
dim2 <- seq(min(x.grid_2_cont), max(x.grid_2_cont), length.out = 25)</pre>
X.grid <- expand.grid(x1 = dim1, x2 = dim2)</pre>
x.grid_3_cont <- as.numeric(rep(mean(stan_dat$total_puts_American$forward_price_scaled[test_start:test_
x.grid_4_cont <- as.numeric(rep(mean(stan_dat$total_puts_American$strike_price[test_start:test_end])),n
x.grid_5_cont <- as.numeric(rep(mean(stan_dat$total_puts_American$dividend_yield_scaled[test_start:test
x.grid_6_cont <- as.numeric(rep(mean(stan_dat$total_puts_American$interest_rate_scaled[test_start:test_
x2_cont <- cbind(X.grid,x.grid_3_cont,x.grid_4_cont,x.grid_5_cont,x.grid_6_cont)</pre>
x.grid_1_cont_bs <- as.numeric(stan_dat$total_puts_American$impl_volatility[test_start:test_end])</pre>
x.grid_2_cont_bs <- as.numeric(stan_dat$total_puts_American$time_to_exp[test_start:test_end])</pre>
x.grid_3_cont_bs <- as.numeric(rep(mean(stan_dat$total_puts_American$forward_price[test_start:test_end]
x.grid_4_cont_bs <- as.numeric(rep(mean(stan_dat$total_puts_American$strike_price[test_start:test_end])
x.grid_5_cont_bs <- as.numeric(rep(mean(stan_dat$total_puts_American$dividend_yield[test_start:test_end
x.grid_6_cont_bs <- as.numeric(rep(mean(stan_dat$total_puts_American$interest_rate[test_start:test_end]
dim1_bs <- seq(min(x.grid_1_cont_bs), max(x.grid_1_cont_bs), length.out = 25)
dim2_bs <- seq(min(x.grid_2_cont_bs),max(x.grid_2_cont_bs),length.out = 25)
X.grid_bs <- expand.grid(x1 = dim1_bs, x2 = dim2_bs)</pre>
x2_cont_bs <- cbind(X.grid_bs,x.grid_3_cont_bs,x.grid_4_cont_bs,x.grid_5_cont_bs,x.grid_6_cont_bs)</pre>
blackscholes_2_cont <- rep(NA,length(x2_cont_bs[,1]))
for (row in 1:nrow(data.frame(x2_cont_bs))){
  blackscholes_2_cont[row] <- as.numeric(blackscholes(-1,S0=x2_cont_bs[row,3],K=x2_cont_bs[row,4],r=x2_
}
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,</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_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:
                          152.694 seconds (Sampling)
                           152.694 seconds (Total)
## Chain 1:
## 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)]

#Computing Standard Deviation
pred_gp_summary_cont <- summary(pred_gp_cont, sd=c("sd"))$summary
pred_gp_sd_cont <- pred_gp_summary_cont[, c("sd")]
y_sd_values_cont <- pred_gp_sd_cont[1:(length(pred_gp_sd_cont)-1)]

par(mfrow = c(1, 2))
#Contour for Predictions aka mean values of predictions
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")</pre>
```





4-3: Contour Plots of Interest Rate & Dividend Yield

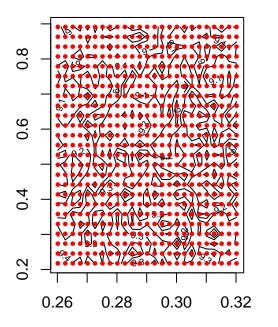
```
x.grid_1_cont <- as.numeric(stan_dat$total_puts_American$dividend_yield_scaled[test_start:test_end])
x.grid_2_cont <- as.numeric(stan_dat$total_puts_American$interest_rate_scaled[test_start:test_end])

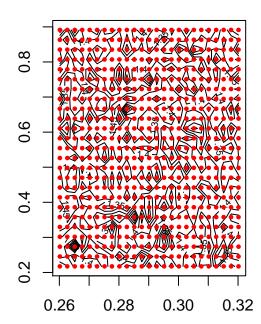
dim1 <- seq(min(x.grid_1_cont), max(x.grid_1_cont), length.out = 25)
dim2 <- seq(min(x.grid_2_cont), max(x.grid_2_cont), length.out = 25)
X.grid <- expand.grid(x1 = dim1, x2 = dim2)

x.grid_3_cont <- as.numeric(rep(mean(stan_dat$total_puts_American$impl_volatility_scaled[test_start:test_end])</pre>
```

```
x.grid_5_cont <- as.numeric(rep(mean(stan_dat$total_puts_American$forward_price_scaled[test_start:test_
x.grid_6_cont <- as.numeric(rep(mean(stan_dat$total_puts_American$strike_price_scaled[test_start:test_e:
x2_cont <- cbind(X.grid,x.grid_3_cont,x.grid_4_cont,x.grid_5_cont,x.grid_6_cont)</pre>
x.grid_1_cont_bs <- as.numeric(stan_dat$total_puts_American$dividend_yield[test_start:test_end])</pre>
x.grid_2_cont_bs <- as.numeric(stan_dat$total_puts_American$interest_rate[test_start:test_end])</pre>
x.grid_3_cont_bs <- as.numeric(rep(mean(stan_dat$total_puts_American$impl_volatility[test_start:test_en
x.grid_4_cont_bs <- as.numeric(rep(mean(stan_dat$total_puts_American$time_to_exp[test_start:test_end]))
x.grid_5_cont_bs <- as.numeric(rep(mean(stan_dat$total_puts_American$forward_price[test_start:test_end]
x.grid_6_cont_bs <- as.numeric(rep(mean(stan_dat$total_puts_American$strike_price[test_start:test_end])</pre>
dim1_bs <- seq(min(x.grid_1_cont_bs), max(x.grid_1_cont_bs), length.out = 25)
dim2_bs <- seq(min(x.grid_2_cont_bs),max(x.grid_2_cont_bs),length.out = 25)
X.grid_bs <- expand.grid(x1 = dim1_bs, x2 = dim2_bs)</pre>
x2_cont_bs <- cbind(X.grid_bs,x.grid_3_cont_bs,x.grid_4_cont_bs,x.grid_5_cont_bs,x.grid_6_cont_bs)
blackscholes_2_cont <- rep(NA,length(x2_cont_bs[,1]))
for (row in 1:nrow(data.frame(x2_cont_bs))){
  blackscholes_2_cont[row] <- as.numeric(blackscholes(-1,S0=x2_cont_bs[row,5],K=x2_cont_bs[row,6],r=x2_
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:
                           152.014 seconds (Sampling)
## Chain 1:
                           152.014 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
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,
               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 0.011 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would take 110 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: 8.793 seconds (Warm-up)
## Chain 1:
                           6.532 seconds (Sampling)
## Chain 1:
                           15.325 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.
##
```

```
##
               mean se_mean
                                 sd
                                         2.5%
                                                  25%
                                                           50%
                                                                   75%
                                                                          97.5%
## theta[1]
                                0.05
                                         0.19
                                                 0.22
                                                          0.26
                                                                  0.29
                                                                          0.38
              0.26
                        0.01
## theta[2]
               4.64
                        0.28
                                1.31
                                         2.63
                                                 3.73
                                                          4.38
                                                                  5.57
                                                                          6.84
## theta[3]
                                                                 12.04
             10.06
                        0.68
                                3.47
                                         5.55
                                                 7.81
                                                          9.02
                                                                         18.58
## theta[4]
               0.37
                        0.01
                                0.08
                                         0.23
                                                 0.31
                                                          0.36
                                                                  0.42
                                                                          0.53
## theta[5]
               1.26
                       0.21
                                0.64
                                         0.65
                                                                  1.52
                                                                          2.98
                                                 0.79
                                                          1.05
## theta[6]
               0.30
                        0.01
                                0.08
                                         0.20
                                                 0.24
                                                          0.28
                                                                  0.36
                                                                          0.50
                                         0.00
               0.00
                                0.00
## sigma2
                        0.00
                                                 0.00
                                                          0.00
                                                                  0.00
                                                                          0.00
## gamma2
            2778.18 252.00 1152.63 1620.56 2011.17 2617.92 3054.29 6466.34
##
            n_eff Rhat
## theta[1]
               83 0.99
               22 1.05
## theta[2]
## theta[3]
               26 1.14
## theta[4]
               82 1.00
## theta[5]
                9 1.23
## theta[6]
               35 0.99
               70 0.98
## sigma2
## gamma2
               21 1.01
##
## Samples were drawn using NUTS(diag_e) at Sun Mar 29 18:49:37 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]) #sigma2</pre>
post_mean_gamma2_SGP <- mean(sum_gp_SGP_European[,1,8]) #qamma2</pre>
post_mean_mu_SGP <- stan_dat_European$blackscholes</pre>
x.grid_1 <- as.numeric(stan_dat$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$impl_volatility_scaled[test_start:test_end])</pre>
x.grid_4 <- as.numeric(stan_dat$total_puts_American$time_to_exp_scaled[test_start:test_end])</pre>
x.grid_5 <- as.numeric(stan_dat$total_puts_American$dividend_yield_scaled[test_start:test_end])</pre>
x.grid_6 <- as.numeric(stan_dat$total_puts_American$interest_rate_scaled[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_Bdrycov
## 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:
                           26.572 seconds (Sampling)
## Chain 1:
                           26.572 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"))$summary</pre>
pred_gp_sd_Bdrycov_disc <- pred_gp_summary_Bdrycov_disc[, c("sd")]</pre>
y_sd_values_Bdrycov_disc <- pred_gp_sd_Bdrycov_disc[1:(length(pred_gp_sd_Bdrycov_disc)-1)]</pre>
3-3: Plotting Predicted Values against Truth
par(mfrow=c(1,4))
#Plotting Standard GP
plot(log(y_mean_values_SGP),log(stan_dat$total_puts_American$mid_price[test_start:test_end]),xlim = c(m
abline(0,1)
#Plotting BDrycov
plot(log(y mean values Bdrycov),log(stan dat$total puts American$mid price[test start:test end]), xlim
abline(0,1)
#Plotting Blackscholes
plot(log(blackscholes_2),log(stan_dat$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
## Warning in log(y_mean_values_Bdrycov_disc): NaNs produced
abline(0,1)
```

