

Augmented Feature Matrix Approach

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First, let's import the necessary packages:

```
library(fields)
library(RandomFields)
library(mvtnorm)
library(ggplot2)
library(matrixcalc)
library(gstat)
library(GpGp)
library(doParallel)
```

Modified function to return augmented feature matrix as discussed with Dr. Sang.

```
augmented_feature_mat <- function(X, locs, knots, phi, sigma_sq){
  C_knots <- sigma_sq*exp(-rdist(knots, knots)/phi)
  half_inv_C_knots <- chol(solve(C_knots))
  basis_X <- sigma_sq*exp(-rdist(locs, knots)/phi)%%half_inv_C_knots
  return(cbind(X, basis_X)[-1])
}
```

Now, let's move on to the more rudimentary functions

```
get_score<- function(y, X, tau, beta){ ## See item (2) below
  n <- nrow(X)
  temp <- t(X[1,,drop=FALSE])*ifelse(y[1] - X[1,,drop=FALSE]%%as.matrix(beta) < 0, tau - 1, tau)[1,1]
  for(i in 2:n){
    temp <- temp + t(X[i,,drop=FALSE])*ifelse(y[i] - X[i,,drop=FALSE]%%as.matrix(beta) < 0, tau - 1, tau)
  }
  return(temp)
}

weight <- function(X, tau){ ## See item (4) below
  n <- nrow(X)
  temp <- X[1,]%%t(X[1,])
  for(i in 2:n){
    temp <- temp + X[i,]%%t(X[i,])
  }
  coef <- n/(tau*(1 - tau))
  return(coef*solve(temp))
}

get_likelihood <- function(y, X, tau, beta, locs, C){ ## See item (5) below
  score <- get_score(y, X, tau, beta)
  coef <- -1/(2*length(y))
```

```

weight_X <- weight(X, tau)
kernel <- exp(coef*(t(score)%*%weight_X%*%score)[1,1])
return(C*kernel)
}

```

A few comments on the methods above:

1. The `augmented_feature_mat()` method was returning a feature matrix with the column of 1s for the intercept. R will include this automatically, so I modified the `return()` statement so the output would not include this column.
2. The `get_score()` function outputs a p length vector whose entries correspond to the features in the feature matrix. The last element in this vector (corresponding to the additional columns we get by appending `X_basis` to our original feature matrix) is much larger than the others, so we should keep an eye on this.
3. I deleted the `get_spatial_covar_mat()` function because we no longer need it.
4. The paper specifies that the weight matrix W must be positive definite. Even though we followed the definition for W given in the paper to a tee, our function doesn't return a positive definite matrix if you consider the eighth decimal place of each entry. Since the eighth decimal isn't especially significant in the grand scheme of things, I added the `round(., 7)` method to make sure that the method returns a weight matrix that satisfies the positive definiteness requirement.
5. I'm not sure how to come up with good values of C in the likelihood function. I've been using $C = 1$ so far just so the code will run and play nice. I need to read through the paper some more to figure out how they did it.

Next, let's look at the methods for the Importance Sampling algorithm for a single quantile.

```

get_updated_params <- function(y, X, tau, beta, Sigma, locs, draws){
  n <- length(y)
  p <- ncol(X)

  is_weights <- numeric(nrow(draws))
  for(i in 1:nrow(draws)){
    is_weights[i] <- get_likelihood(y, X, tau, draws[i,], locs, 1)*(1/(2*n)^p)/dmvnorm(draws[i,], beta,
  }

  mu_hat <- apply(w*draws, 2, sum)/sum(w)

  S <- matrix(nrow = p, ncol = p)
  for(i in 1:p){
    for(j in 1:p){
      S[i,j] <- sum(w*draws[,i]*draws[,j])/sum(w) - mu_hat[i]*mu_hat[j]
    }
  }
  temp <- list(mu_hat, S)
  names(temp) <- c("mu", "S")
  return(temp)
}

adaIS_singleQuantile <- function(y, X, tau, C, locs, M, num_reps){
  p <- ncol(X) ## Step 1: Initialize starting values for IS algorithm
  n <- length(y) ## Step 1: Initialize starting values for IS algorithm
  beta <- coef(lm(y ~ X))[-1] ## Step 1: Initialize starting values for IS algorithm
  S <- cov(X) ## Step 1: Initialize starting values for IS algorithm

  a_1 <- coef(lm(y ~ X))[-1]

```

```

a_0 <- quantile(y - X%%a_1, tau)
a <- c(a_0, a_1)
X <- cbind(rep(1, n), X)
temp <- X[1,]%%t(X[1,])
for(i in 2:n){
  temp <- temp + X[i,]%%t(X[i,])
}
S_0 <- 1*tau*(1 - tau)*solve((1/n)*temp)

params <- list(a, S_0)
names(params) <- c("mu", "S")
draw <- rmvnorm(M, params$mu, params$S)

# params <- list(beta, S) ## Put our initial parameter estimates/starting values into a list called
# names(params) <- c("mu", "S")

for(i in 2:num_reps){ ## Step 4: Repeat steps 2 and 3 until we achieve the desired effective sample size
  draw <- rmvnorm(M, params$mu, params$S) ## Step 2: Simulate M values from the proposal distribution
  params <- get_updated_params(y, X, tau, params$mu, params$S, locs, draw) ## Step 3: Update the parameters
}
return(params)
}

```

Next, let's simulate some data so we can test what we have so far.

First, let's generate and plot the simulated data.

```

n <- 10000
locs <- as.matrix(cbind(runif(n, 0, 10), runif(n, 0, 10)))
sigma_sq <- 2
phi <- 5
nu <- .5
tau_sq <- .5

w <- fast_Gp_sim(c(sigma_sq, phi, nu, 0), "matern_isotropic", locs, 30)

X <- as.matrix(cbind(rep(1, n), locs[,1]/10, locs[,2]/10))
beta <- as.matrix(c(1, 2, 3))
p <- length(beta)
y <- rnorm(n, X%%beta + w, sqrt(tau_sq))

training_indices <- sample(1:n, round(.75*n), replace = FALSE)

y_train <- y[training_indices]
X_train <- X[training_indices,]
locs_train <- locs[training_indices,]

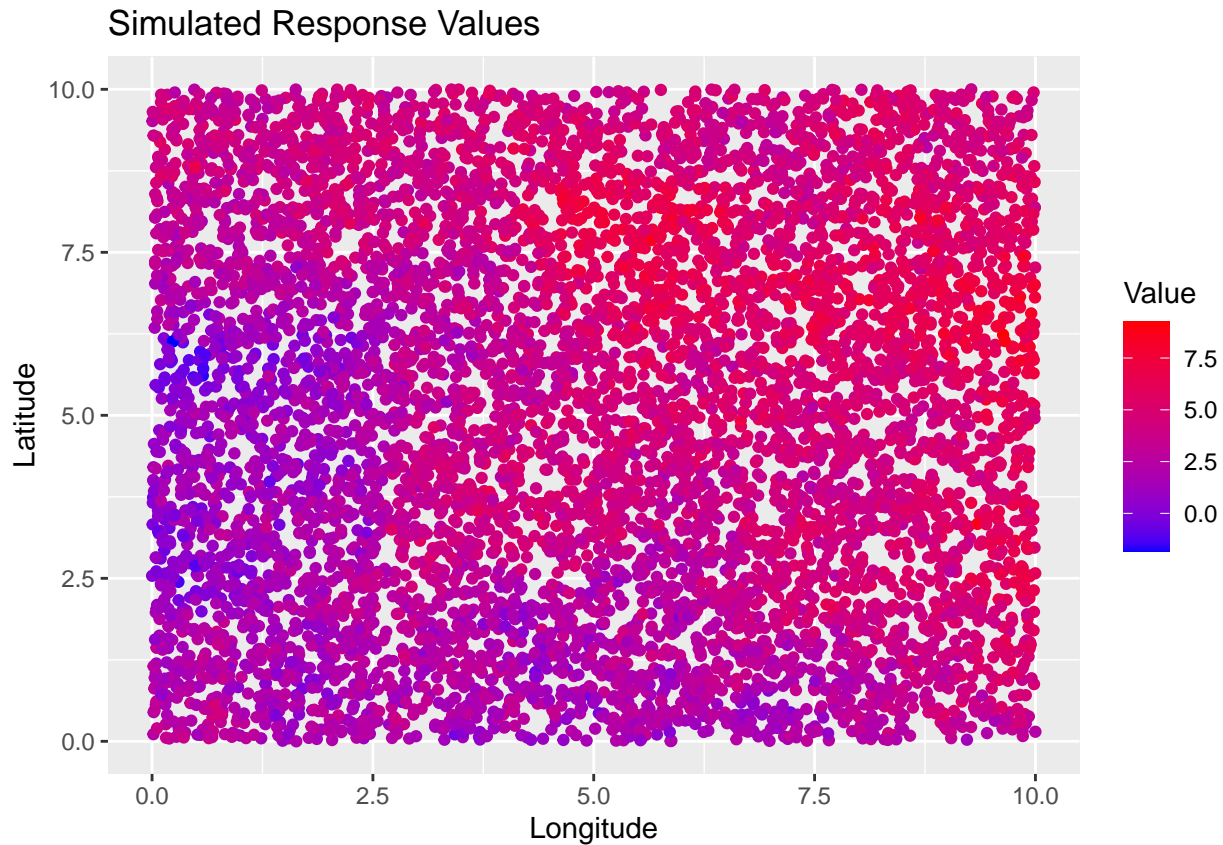
y_test <- y[-training_indices]
X_test <- X[-training_indices,]
locs_test <- locs[-training_indices,]

training_data <- as.data.frame(cbind(y_train, X_train[, -1], locs_train))
names(training_data) <- c("y_train", "X1_train", "X2_train", "long_train", "lat_train")

ggplot() + geom_point(data = training_data, aes(x = long_train, y = lat_train, col = y_train)) +

```

```
scale_colour_gradient(low = "blue", high = "red") +
labs(title = "Simulated Response Values",
     x = "Longitude",
     y = "Latitude",
     col = "Value")
```



Next, let's test out our more basic methods.

```
tau <- .5
```

```
X_augmented <- augmented_feature_mat(X_train, locs_train, expand.grid(seq(0.1,9.9,length=5),seq(0.1,9.9
X_augmented[1:10,]
```

```
##           [,1]      [,2]      [,3]      [,4]      [,5]      [,6]      [,7]
## [1,] 0.90144636 0.38017481 0.2907133 0.3414128 0.5046459 0.6436942 0.49466345
## [2,] 0.34046266 0.09971688 1.0102839 1.1807000 0.7855979 0.3292099 0.13831739
## [3,] 0.86672374 0.31800177 0.3244146 0.3863848 0.5801539 0.7436754 0.52769288
## [4,] 0.21349409 0.91212062 0.3152171 0.2059022 0.1755485 0.1293384 0.06923943
## [5,] 0.03825113 0.39167863 0.9320539 0.4650838 0.2820765 0.1642182 0.07081242
## [6,] 0.34693320 0.09757940 0.9988226 1.1756822 0.8086337 0.3337296 0.14030687
## [7,] 0.99866654 0.63957727 0.1922174 0.2122398 0.2955678 0.3636075 0.31244149
## [8,] 0.42445405 0.56524650 0.5012441 0.4338743 0.4140102 0.3022069 0.15051588
## [9,] 0.34310562 0.24936996 0.8822297 0.8646122 0.6680751 0.3435577 0.14219668
## [10,] 0.08506097 0.89480599 0.3392943 0.1973135 0.1566782 0.1095377 0.05608016
##           [,8]      [,9]      [,10]      [,11]      [,12]      [,13]
## [1,] 0.05126766 0.07047130 0.221054320 0.539005951 0.363663622 0.026117028
## [2,] 0.11752958 0.18500384 0.057725118 -0.064139970 -0.095253754 -0.002561044
## [3,] 0.04452468 0.06251096 0.227880898 0.623624910 0.285259825 0.015634216
```

```
## [4,] 0.28272789 0.15036538 0.111688303 0.064660673 0.004849260 0.457451941
## [5,] 0.90985730 0.16030779 0.001838208 -0.007755388 -0.040815455 0.706769191
## [6,] 0.10992524 0.17529704 0.062934258 -0.064638159 -0.096449729 -0.002985362
## [7,] 0.06228550 0.07559060 0.166390853 0.301453379 0.258557029 0.057608245
## [8,] 0.32014683 0.33934728 0.330147442 0.140291172 -0.016248229 0.317291242
## [9,] 0.32667869 0.61351566 0.244775336 -0.043909565 -0.086123790 0.048067642
## [10,] 0.32048372 0.13108321 0.083441688 0.043918267 -0.002311292 0.540302911
##      [,14]      [,15]      [,16]      [,17]      [,18]
## [1,] 0.04315400 0.127051225 0.381286654 0.156828209 -0.002995504
## [2,] -0.02232433 -0.009797530 0.008223273 -0.051801849 -0.001710911
## [3,] 0.02445579 0.080467665 0.255534948 -0.017382638 -0.004087791
## [4,] 0.29609064 0.178406828 0.083446631 -0.003361837 0.640640797
## [5,] 0.06875451 -0.009448854 0.006422083 -0.033892343 0.062592405
## [6,] -0.02196064 -0.010070285 0.008235665 -0.052313660 -0.001931041
## [7,] 0.08888984 0.205148873 0.464129095 0.518605938 0.021861733
## [8,] 0.54453330 0.624997936 0.058779166 -0.057689149 0.095161030
## [9,] 0.05746052 0.039343251 0.005665803 -0.058603749 -0.001417858
## [10,] 0.23802662 0.115582252 0.053325121 -0.008790862 0.862208418
##      [,19]      [,20]      [,21]      [,22]      [,23]
## [1,] -0.004694600 -0.006329020 0.0358221999 -0.15009105 0.0154114528
## [2,] -0.002565537 -0.003779586 0.0077263281 -0.04168996 0.0008642146
## [3,] -0.004442577 -0.006735395 0.0292175523 -0.12772399 0.0136082040
## [4,] 0.533900564 0.143326624 0.0348537398 -0.03833879 0.4097004612
## [5,] -0.023330185 -0.009637151 0.0009372025 -0.03465187 0.0050569469
## [6,] -0.002522743 -0.003744866 0.0078902211 -0.04194529 0.0009648892
## [7,] 0.034901210 0.095665585 0.2972285179 0.32726684 0.0211992440
## [8,] 0.170119230 0.176669211 0.0011442769 -0.08207209 0.0068209530
## [9,] -0.009889336 -0.009067305 0.0056172413 -0.05090298 0.0021703751
## [10,] 0.308069488 0.050256116 0.0169907153 -0.03371836 0.5887477002
##      [,24]      [,25]      [,26]      [,27]
## [1,] -0.01225382 -0.02848270 -0.02423855 -0.22048491
## [2,] -0.03291880 -0.03886125 -0.03008973 -0.08016138
## [3,] -0.01305396 -0.02807303 -0.02339336 -0.19102709
## [4,] 0.24205697 -0.28072477 -0.17065615 -0.18083448
## [5,] -0.09126103 -0.07501490 -0.04898021 -0.07899751
## [6,] -0.03246958 -0.03854836 -0.02991050 -0.08047853
## [7,] -0.01328062 -0.03664738 -0.04749605 -0.39203985
## [8,] -0.09612295 -0.12692491 -0.10766943 -0.19137831
## [9,] -0.04617170 -0.05506727 -0.04375936 -0.10325600
## [10,] -0.12297757 -0.23777947 -0.12290926 -0.13513375
```

```
beta <- coef(lm(y_train ~ X_augmented))[-1]
score <- get_score(y_train, X_augmented, tau, beta)
score
```

```
##      [,1]
## [1,] 1864.00762
## [2,] 1866.81891
## [3,] 1991.73937
## [4,] 1716.82390
## [5,] 1712.36437
## [6,] 1449.54222
## [7,] 799.60466
## [8,] 916.29598
## [9,] 684.70563
```

```
## [10,] 710.53469
## [11,] 625.14678
## [12,] 60.32692
## [13,] 812.77319
## [14,] 711.33975
## [15,] 729.26241
## [16,] 664.59325
## [17,] 15.08519
## [18,] 551.54475
## [19,] 478.10161
## [20,] 460.27955
## [21,] 446.08022
## [22,] -116.73378
## [23,] 219.94426
## [24,] -116.38366
## [25,] -208.47069
## [26,] -193.72344
## [27,] -725.31154
```

```
weight_mat <- weight(X_augmented, tau)
weight_mat
```

```
##           [,1]      [,2]      [,3]      [,4]      [,5]      [,6]
## [1,] 89491.987 -18960.555 4219.41706 -10926.1884 -18070.3015 -28048.8122
## [2,] -18960.555 94432.500 -3119.73446 -2893.1454 -1403.1551 1133.0285
## [3,] 4219.417 -3119.734 538.21075 -723.3845 -628.6716 -1228.3546
## [4,] -10926.188 -2893.145 -723.38453 2255.0395 2156.6646 3825.2282
## [5,] -18070.302 -1403.155 -628.67162 2156.6646 4457.9046 5606.8067
## [6,] -28048.812 1133.028 -1228.35463 3825.2282 5606.8067 9616.2240
## [7,] -47017.687 5775.315 -2101.82384 5928.7461 9856.5952 14491.7145
## [8,] 6191.332 -21135.926 517.68202 611.2778 -123.8489 -872.0660
## [9,] -5091.207 -16697.253 338.28405 1398.3462 2152.7434 2554.6701
## [10,] -8179.046 -16100.860 58.82732 2119.1380 2475.2399 3630.7237
## [11,] -13330.290 -15116.200 -182.83143 2671.8633 3826.2880 4942.3561
## [12,] -29793.457 -11928.941 -946.32664 4706.8178 7089.6832 10554.5612
## [13,] 5782.688 -26669.358 987.79853 712.7264 296.4243 -454.4369
## [14,] -6931.080 -18707.972 147.85911 2072.2584 2559.2761 3233.0029
## [15,] -11197.410 -18462.570 -21.82514 2557.2552 3540.5230 4604.5580
## [16,] -16739.259 -17360.531 -269.71812 3241.2723 4573.1775 6410.8450
## [17,] -30841.299 -17568.784 -854.00707 5169.4546 7620.7501 10946.8640
## [18,] 6482.060 -35715.077 1125.03522 1208.4183 690.0899 -198.0729
## [19,] -7657.090 -23749.193 271.72125 2380.1701 3020.4776 3760.8159
## [20,] -11486.123 -24332.169 126.85107 2952.9926 3856.7474 5043.5590
## [21,] -16476.712 -22482.284 -129.49503 3522.3032 4846.5347 6545.1560
## [22,] -29762.988 -24276.663 -651.78205 5395.0989 7785.9602 10962.9354
## [23,] 9114.613 -53489.723 1711.60188 1857.2375 1143.0431 -111.6175
## [24,] -8868.276 -33146.836 454.47792 3115.7766 3827.5004 4645.6517
## [25,] -13519.118 -34018.038 281.47804 3792.7448 4894.3269 6220.8699
## [26,] -19480.818 -31732.977 -30.88811 4445.6598 6008.7790 8021.1186
## [27,] -29640.010 -31927.834 -411.40393 5881.5738 8270.2705 11418.9761
##           [,7]      [,8]      [,9]      [,10]      [,11]      [,12]
## [1,] -47017.687 6191.3323 -5091.2070 -8179.04559 -13330.2901 -29793.4566
## [2,] 5775.315 -21135.9260 -16697.2532 -16100.86025 -15116.1998 -11928.9414
## [3,] -2101.824 517.6820 338.2841 58.82732 -182.8314 -946.3266
## [4,] 5928.746 611.2778 1398.3462 2119.13803 2671.8633 4706.8178
```

##	[5,]	9856.595	-123.8489	2152.7434	2475.23990	3826.2880	7089.6832
##	[6,]	14491.714	-872.0660	2554.6701	3630.72375	4942.3561	10554.5612
##	[7,]	25627.487	-2331.6771	3490.7983	5129.58546	7878.6400	16069.6389
##	[8,]	-2331.677	5291.9724	3292.2456	3398.01801	2992.5864	1947.9599
##	[9,]	3490.798	3292.2456	4279.9879	3793.22962	4341.9390	5263.9142
##	[10,]	5129.585	3398.0180	3793.2296	4725.57979	4571.7970	6408.5840
##	[11,]	7878.640	2992.5864	4341.9390	4571.79703	6001.4460	7870.2080
##	[12,]	16069.639	1947.9599	5263.9142	6408.58399	7870.2080	14501.1268
##	[13,]	-1857.305	5670.9631	4792.0074	4476.40157	4196.4625	3209.7129
##	[14,]	4584.172	4036.6714	4161.5324	4648.35394	5048.1534	6365.8865
##	[15,]	6857.503	3795.3515	4775.4714	4952.00831	5855.4833	7933.4133
##	[16,]	9764.380	3434.9915	5075.0319	5697.14319	6476.4248	9758.4327
##	[17,]	17460.727	3166.1926	6514.0846	7596.56948	9477.0865	14791.8802
##	[18,]	-1808.587	8094.3070	6369.1678	6183.63562	5858.1532	4775.0311
##	[19,]	5203.878	5029.7109	5484.8520	5713.38349	6173.5168	7674.7709
##	[20,]	7294.311	5071.3455	5927.9868	6408.10232	7036.2955	9240.4427
##	[21,]	9873.032	4567.9525	6053.9564	6647.95751	7685.4341	10762.5201
##	[22,]	17019.355	4640.1312	7705.7294	8744.24935	10511.4661	16182.6233
##	[23,]	-2396.466	11892.2906	9618.8613	9337.35040	8876.3093	7369.3813
##	[24,]	6287.678	7085.4295	7377.8296	7719.80265	8278.5345	10017.2192
##	[25,]	8834.872	7178.6968	8044.9066	8509.69735	9358.7738	11966.0983
##	[26,]	11899.039	6524.0051	8171.4915	8862.40212	9987.7593	13683.7038
##	[27,]	17459.325	6392.0395	9290.6634	10375.59462	12140.9639	17682.7876
##	[,13]	[,14]	[,15]	[,16]	[,17]	[,18]	
##	[1,]	5782.6881	-6931.0796	-11197.41036	-16739.2588	-30841.2989	6482.0595
##	[2,]	-26669.3581	-18707.9720	-18462.57013	-17360.5306	-17568.7836	-35715.0773
##	[3,]	987.7985	147.8591	-21.82514	-269.7181	-854.0071	1125.0352
##	[4,]	712.7264	2072.2584	2557.25523	3241.2723	5169.4546	1208.4183
##	[5,]	296.4243	2559.2761	3540.52302	4573.1775	7620.7501	690.0899
##	[6,]	-454.4369	3233.0029	4604.55797	6410.8450	10946.8640	-198.0729
##	[7,]	-1857.3050	4584.1718	6857.50278	9764.3796	17460.7268	-1808.5866
##	[8,]	5670.9631	4036.6714	3795.35149	3434.9915	3166.1926	8094.3070
##	[9,]	4792.0074	4161.5324	4775.47144	5075.0319	6514.0846	6369.1678
##	[10,]	4476.4016	4648.3539	4952.00831	5697.1432	7596.5695	6183.6356
##	[11,]	4196.4625	5048.1534	5855.48327	6476.4248	9477.0865	5858.1532
##	[12,]	3209.7129	6365.8865	7933.41333	9758.4327	14791.8802	4775.0311
##	[13,]	8033.9767	4987.3289	5216.42284	4790.1813	4817.9219	9795.9611
##	[14,]	4987.3289	5536.9497	5351.43962	6038.8674	7771.6332	7301.6829
##	[15,]	5216.4228	5351.4396	6631.57351	6769.6274	9532.7411	7103.2398
##	[16,]	4790.1813	6038.8674	6769.62740	8391.5180	11201.0456	6751.5240
##	[17,]	4817.9219	7771.6332	9532.74108	11201.0456	17914.0810	6943.8086
##	[18,]	9795.9611	7301.6829	7103.23976	6751.5240	6943.8086	13995.5660
##	[19,]	6717.6900	6073.9099	6858.06631	7323.0744	9422.1216	8850.1952
##	[20,]	6788.5623	6901.1552	7447.92873	8413.8372	11144.4325	9399.9476
##	[21,]	6255.9780	7098.2051	8106.80905	8977.3079	12647.5994	8673.1861
##	[22,]	6674.7457	9119.6392	10749.12385	12709.2525	18074.6643	9456.8071
##	[23,]	15224.0128	10796.0891	10755.29337	10234.1900	10630.8636	19905.2266
##	[24,]	9313.3285	8610.5502	9217.74539	9773.4811	12434.1714	12854.2060
##	[25,]	9530.7245	9326.9461	10334.69561	11121.7241	14590.1007	13068.7241
##	[26,]	8851.4484	9525.4206	10714.11332	12021.9907	16338.5256	12231.5502
##	[27,]	8921.1748	10960.8559	12694.58781	14629.8412	20863.8005	12477.2837
##	[,19]	[,20]	[,21]	[,22]	[,23]	[,24]	
##	[1,]	-7657.0903	-11486.1226	-16476.712	-29762.988	9114.6130	-8868.2760
##	[2,]	-23749.1932	-24332.1693	-22482.284	-24276.663	-53489.7231	-33146.8356

##	[3,]	271.7213	126.8511	-129.495	-651.782	1711.6019	454.4779
##	[4,]	2380.1701	2952.9926	3522.303	5395.099	1857.2375	3115.7766
##	[5,]	3020.4776	3856.7474	4846.535	7785.960	1143.0431	3827.5004
##	[6,]	3760.8159	5043.5590	6545.156	10962.935	-111.6175	4645.6517
##	[7,]	5203.8779	7294.3110	9873.032	17019.355	-2396.4655	6287.6784
##	[8,]	5029.7109	5071.3455	4567.952	4640.131	11892.2906	7085.4295
##	[9,]	5484.8520	5927.9868	6053.956	7705.729	9618.8613	7377.8296
##	[10,]	5713.3835	6408.1023	6647.958	8744.249	9337.3504	7719.8026
##	[11,]	6173.5168	7036.2955	7685.434	10511.466	8876.3093	8278.5345
##	[12,]	7674.7709	9240.4427	10762.520	16182.623	7369.3813	10017.2192
##	[13,]	6717.6900	6788.5623	6255.978	6674.746	15224.0128	9313.3285
##	[14,]	6073.9099	6901.1552	7098.205	9119.639	10796.0891	8610.5502
##	[15,]	6858.0663	7447.9287	8106.809	10749.124	10755.2934	9217.7454
##	[16,]	7323.0744	8413.8372	8977.308	12709.253	10234.1900	9773.4811
##	[17,]	9422.1216	11144.4325	12647.599	18074.664	10630.8636	12434.1714
##	[18,]	8850.1952	9399.9476	8673.186	9456.807	19905.2266	12854.2060
##	[19,]	8249.9864	8311.1388	8787.277	11086.516	13793.1605	10349.4053
##	[20,]	8311.1388	9846.2752	9662.923	12935.768	14058.0653	11549.3922
##	[21,]	8787.2771	9662.9226	11006.774	14062.926	13159.1951	11716.6796
##	[22,]	11086.5158	12935.7681	14062.926	20893.753	14388.1334	14739.3346
##	[23,]	13793.1605	14058.0653	13159.195	14388.133	30939.6351	18824.9236
##	[24,]	10349.4053	11549.3922	11716.680	14739.335	18824.9236	15316.2219
##	[25,]	11649.2733	12454.2858	13221.066	16946.351	19824.5196	15423.1490
##	[26,]	11763.9581	13231.3224	13701.696	18441.054	18459.8089	15966.0700
##	[27,]	13426.8141	15368.7143	16984.016	22617.409	18912.2804	17892.4493
##	[,25]	[,26]	[,27]				
##	[1,]	-13519.118	-19480.81840	-29640.0105			
##	[2,]	-34018.038	-31732.97724	-31927.8340			
##	[3,]	281.478	-30.88811	-411.4039			
##	[4,]	3792.745	4445.65982	5881.5738			
##	[5,]	4894.327	6008.77903	8270.2705			
##	[6,]	6220.870	8021.11857	11418.9761			
##	[7,]	8834.872	11899.03938	17459.3248			
##	[8,]	7178.697	6524.00506	6392.0395			
##	[9,]	8044.907	8171.49152	9290.6634			
##	[10,]	8509.697	8862.40212	10375.5946			
##	[11,]	9358.774	9987.75929	12140.9639			
##	[12,]	11966.098	13683.70380	17682.7876			
##	[13,]	9530.725	8851.44841	8921.1748			
##	[14,]	9326.946	9525.42062	10960.8559			
##	[15,]	10334.696	10714.11332	12694.5878			
##	[16,]	11121.724	12021.99073	14629.8412			
##	[17,]	14590.101	16338.52564	20863.8005			
##	[18,]	13068.724	12231.55020	12477.2837			
##	[19,]	11649.273	11763.95808	13426.8141			
##	[20,]	12454.286	13231.32241	15368.7143			
##	[21,]	13221.066	13701.69630	16984.0162			
##	[22,]	16946.351	18441.05375	22617.4089			
##	[23,]	19824.520	18459.80889	18912.2804			
##	[24,]	15423.149	15966.06997	17892.4493			
##	[25,]	18025.800	17351.22775	20595.9999			
##	[26,]	17351.228	19224.02880	21630.1487			
##	[27,]	20596.000	21630.14873	28393.8946			


```
lik <- get_likelihood(y_train, X_augmented, tau, beta, locs_train, 1)
lik
```

```
## [1] 0
```

As can be seen above, the code for the more basic methods runs. However, we still run into the same issues we discussed earlier.

Now, let's move on to the Importance Sampling methods.

```
Sigma <- cov(X_augmented)
draw <- rmvnorm(1000, beta, Sigma)
## pars <- get_updated_params(y_train, X_augmented, tau, beta, Sigma, locs_train, draw)
## pars

## post_dist_params <- adaIS_singleQuantile(y_train, X_augmented, tau, 1, locs_train, 5000, 10)
## get_updated_params() isn't working, so we can't expect adaIS_singleQuantile() to work either
```

Because this is a Bayesian regression model, we will need to derive the posterior predictive distribution to make predictions at the test locations using the test data. Once the Importance Sampling methods work and give us proper values for the parameters of the posterior distribution, we can make the desired predictions to evaluate the predictive performance of our model.