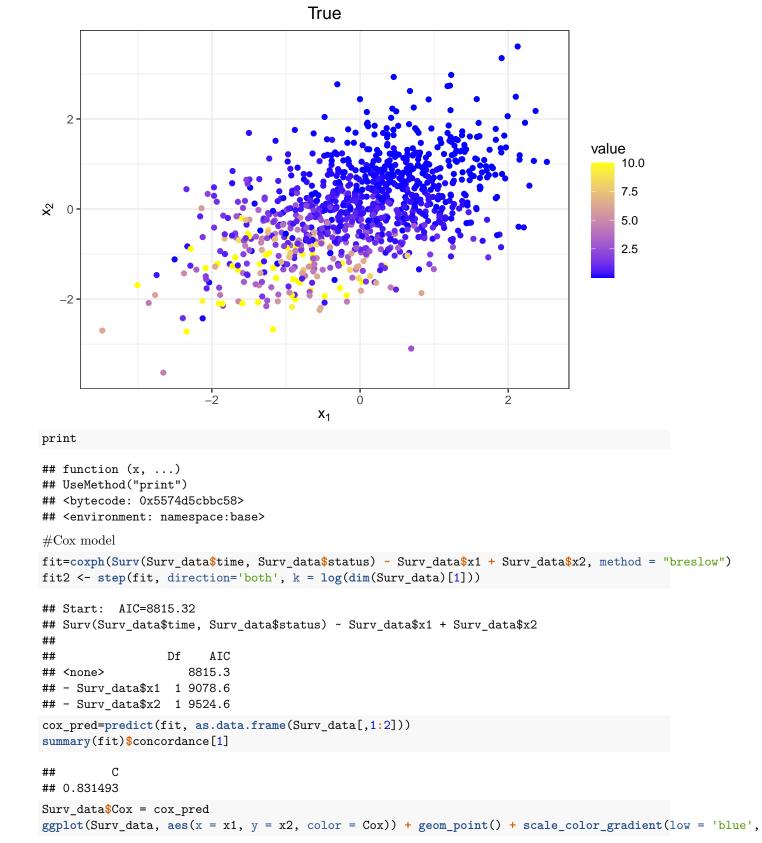
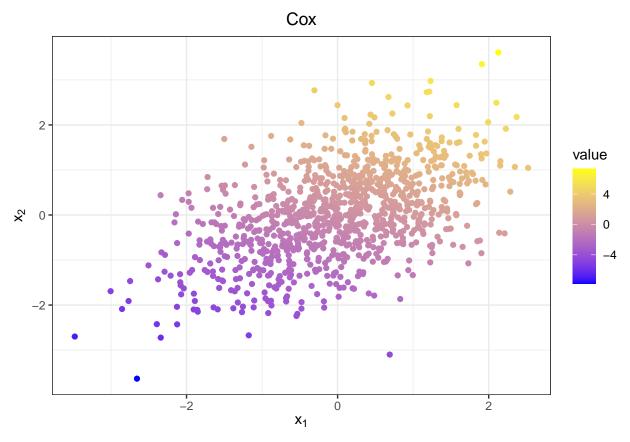
MKL Cox (MKCox)

We will be mimicing example 1, two factors with linear relatophsip with the hazard function $h(X) = (X_1 + 2 * X_2)$, from 'Fenchel duality of Cox partial likelihood and its application in survival kernel learning' Wilson et. al (2020).

Loading data and plotting data

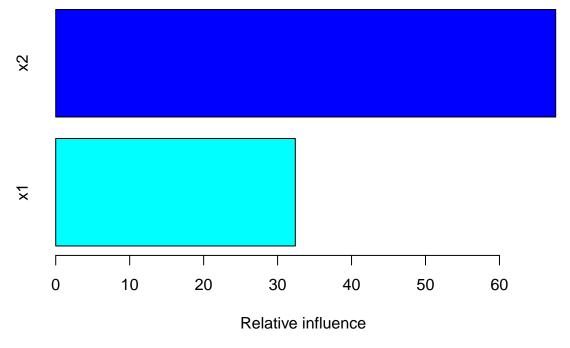
```
library(RMKL)
library(ggplot2)
library(survival)
library(gbm)
## Loaded gbm 2.1.5
library(randomForestSRC)
##
##
   randomForestSRC 2.9.3
##
   Type rfsrc.news() to see new features, changes, and bug fixes.
##
library(kernlab)
##
## Attaching package: 'kernlab'
## The following object is masked from 'package:ggplot2':
##
##
       alpha
data(Surv_data)
head(Surv_data)
              x1
                         x2
                                   time status
## 1 0.70152066 0.8990872 0.040041376
                                          TRUE
## 2 -0.21223395 -0.6490695 1.230534188
                                          TRUE
## 3 -0.08404824 1.4702301 0.005509966
                                          TRUE
## 4 0.86906459 0.4015776 0.437023163
                                          TRUE
## 5 -1.88954937 -1.9095317 4.220627369
                                          TRUE
## 6 -0.58108709 0.1864732 0.138348879
                                          TRUE
ggplot(Surv_data, aes(x = x1, y = x2, color = time)) + geom_point() + scale_color_gradient(low = 'blue'
labs(color = 'value', title = 'True', x = expression(x[1]), y = expression(x[2])) + theme_bw() + theme(p
```





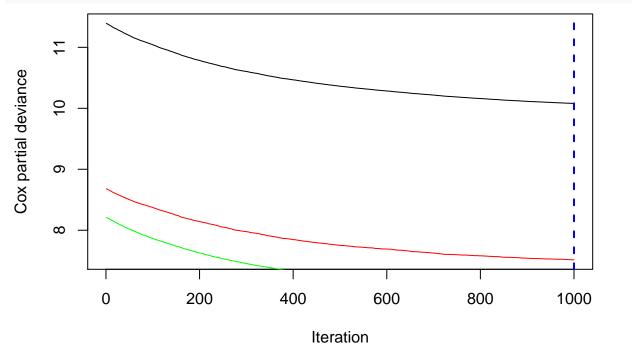
#Gradient Boosting

```
gbm1 <- gbm(Surv(time, status) ~ x1 + x2,</pre>
                                                 # formula
              data=Surv_data,
                                               # dataset
              distribution="coxph",
              n.trees=1000,
                                         # number of trees
              shrinkage=0.005,
                                         # shrinkage or learning rate, 0.001 to 0.1 usually work
                                         # 1: additive model, 2: two-way interactions, etc
              interaction.depth=1,
                                        # subsampling fraction, 0.5 is probably best
              bag.fraction = 0.5,
              train.fraction = 0.8,
                                         \# fraction of data for training, first train.fraction*N used f
              cv.folds = 5,
                                         \# do 5-fold cross-validation
              verbose = F)
                                     # print progress
summary(gbm1)
```

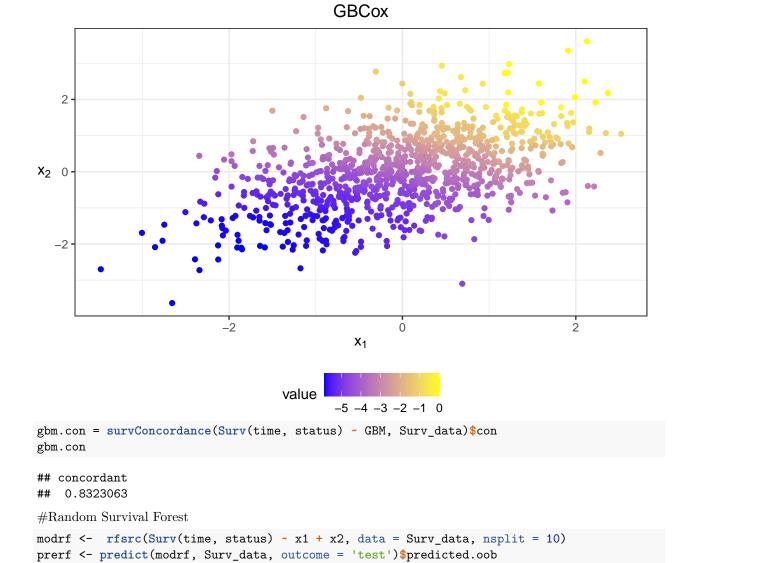


var rel.inf ## x2 x2 67.60328 ## x1 x1 32.39672

best.iter <- gbm.perf(gbm1,method = "cv")</pre>

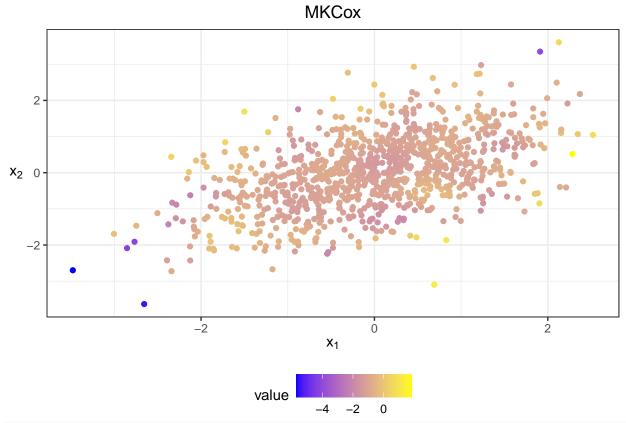


gpred2=predict(gbm1,Surv_data,best.iter)
Surv_data\$GBM = gpred2
ggplot(Surv_data, aes(x = x1, y = x2, color = GBM)) + geom_point() + scale_color_gradient(low = 'blue',



ggplot(Surv_data, aes(x = x1, y = x2, color = RSF)) + geom_point() + scale_color_gradient(low = 'blue',

Surv_data\$RSF = prerf



MKCox.con = survConcordance(Surv(time, status) ~ MKCox, Surv_data)\$con
MKCox.con

concordant ## 0.5566168