Sick dataset analysis

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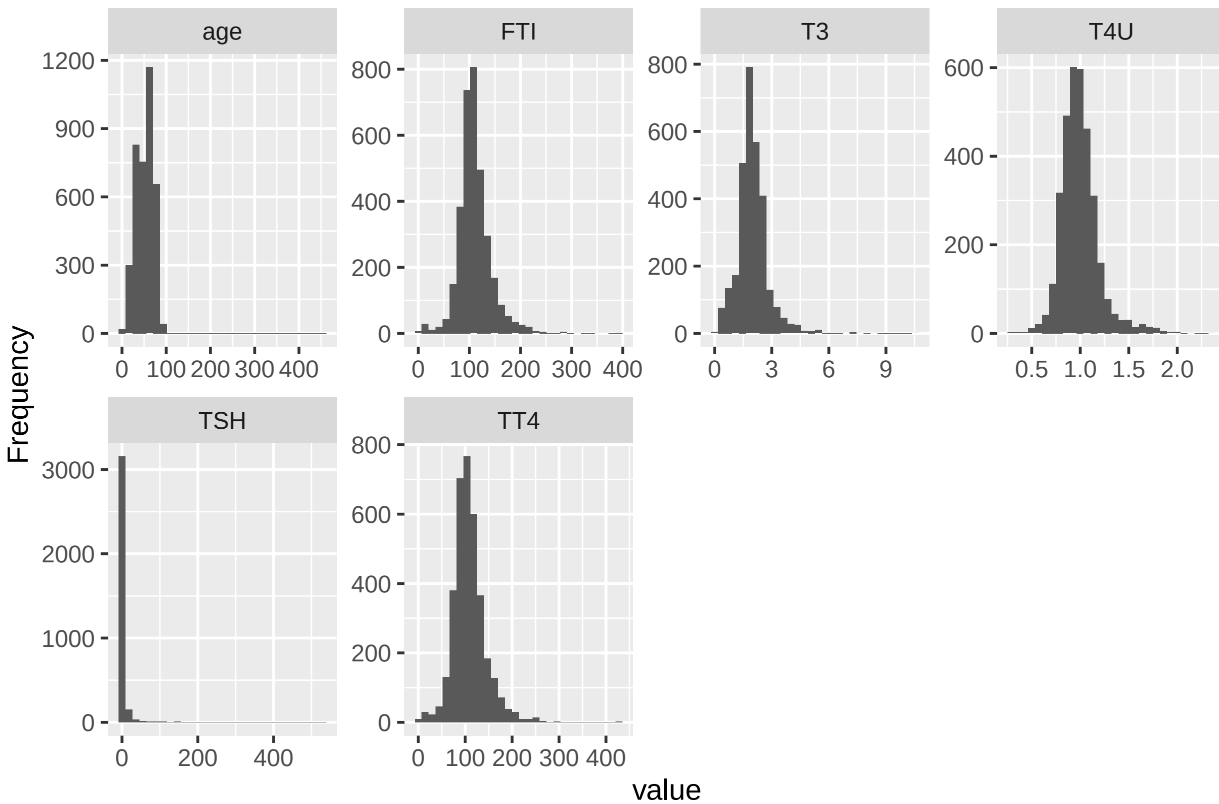
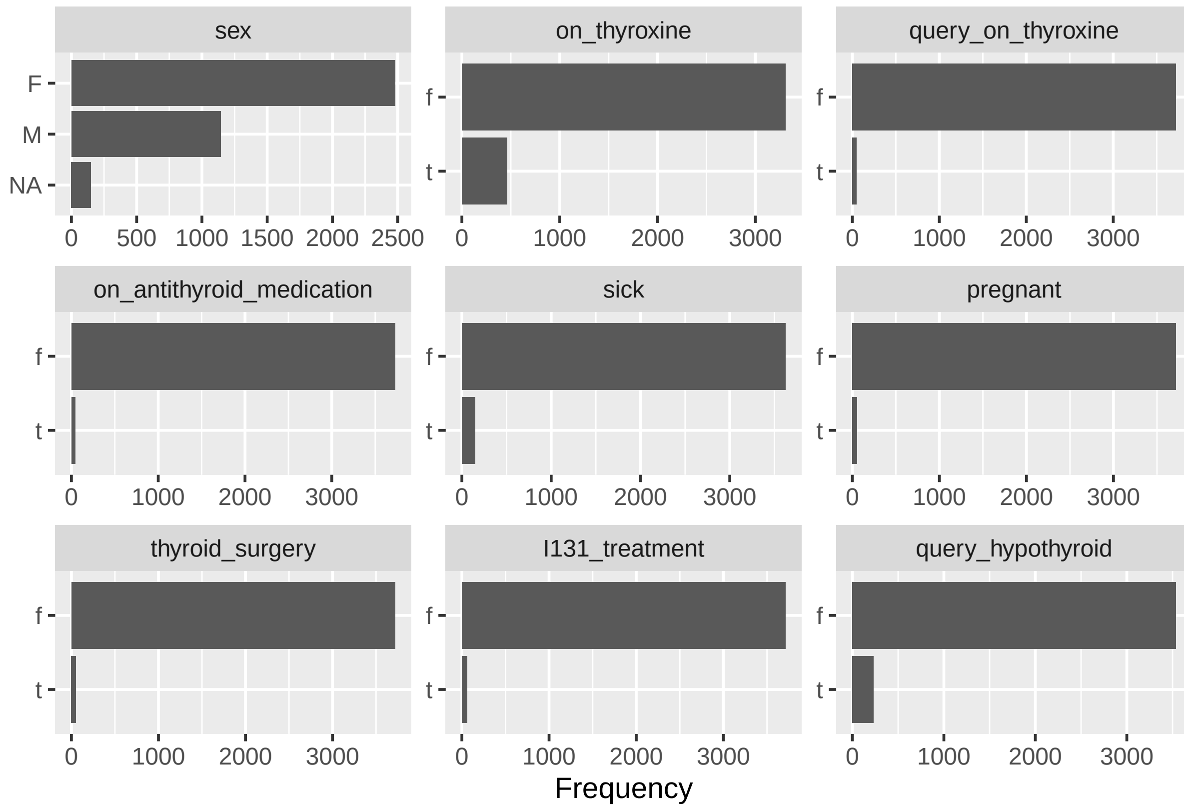
```r
DataExplorer::plot_histogram(dataset_raw)
```




```r
DataExplorer::plot_bar(dataset_raw)
```


sex
on_thyroxine
query_on_thyroxine
on_antithyroid_medication
sick
pregnant
thyroid_surgery
I131_treatment
query_hypothyroid
F
M
NA
f
t
0
500
1000
1500
2000
2500
3000
Frequency

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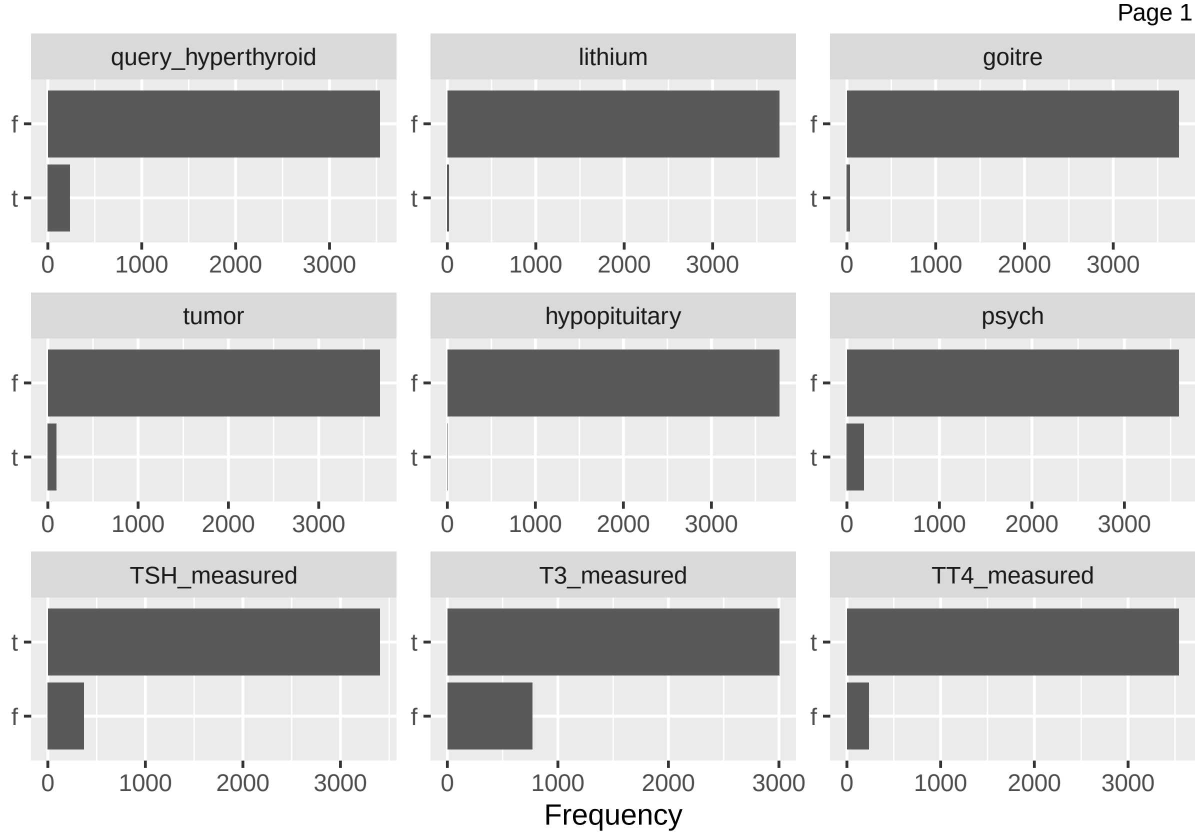
query_hyperthyroid
lithium
goitre
tumor
hypopituitary
psych
TSH_measured
T3_measured
TT4_measured
f
t
0
1000
2000
3000
Frequency

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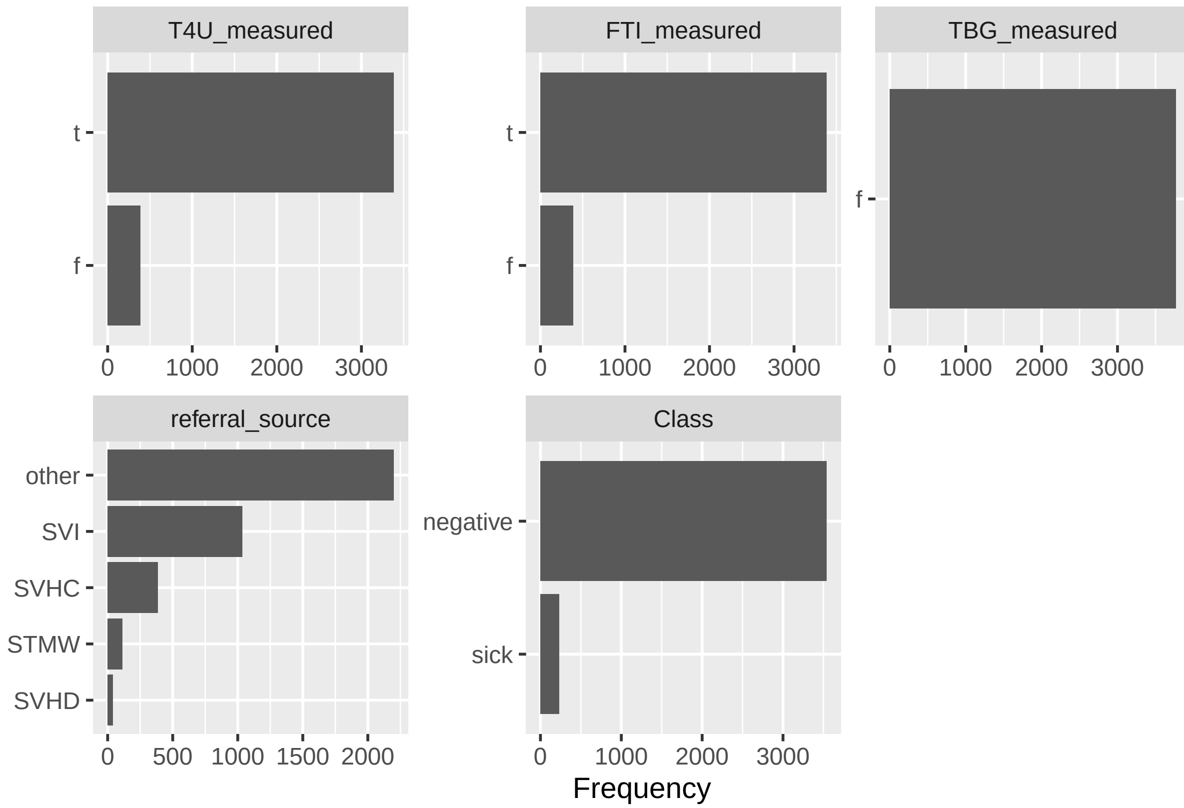

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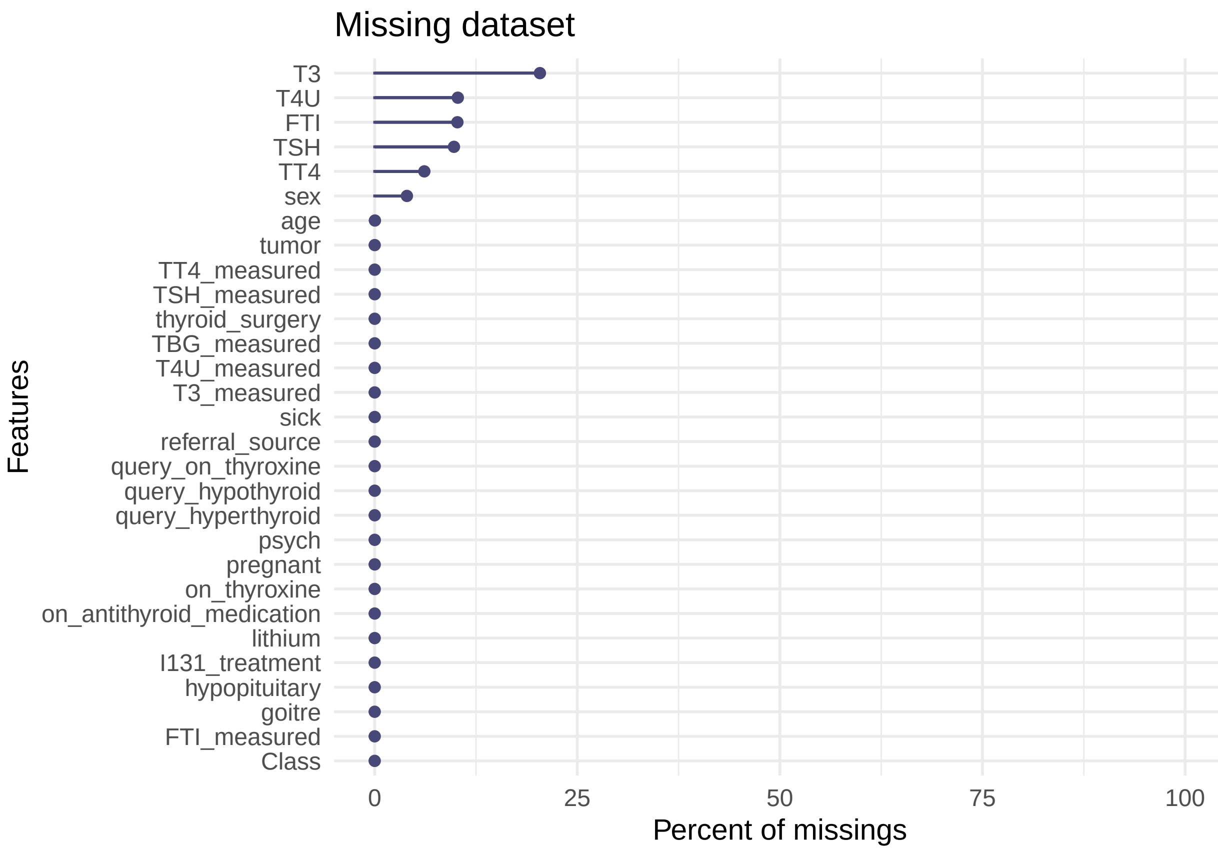
Preprocessing

```
gg_miss_var(dataset,
            show_pct = TRUE) +
  ylim(0, 100) +
  labs(title = "Missing dataset",
       x = "Features",
       y = "Percent of missings")
```




```
# 80% train i 20% test data

# cross-validation
```

As we can see our dataset is very imbalanced on 3772 people only 231 are sick. So we are going to use AUC and AUPRC measures. Let us split our dataset to training and testing parts according to the file.

```
sick <- suppressMessages(read_csv("dataset_38_sick.csv"))
sick<-sick %>%
  mutate_if(is.character, list(~na_if(., "?")))
sick<-suppressMessages(type_convert(sick))
sick<-DataExplorer::drop_columns(sick,c("TBG","hypopituitary"))
sick<-sick %>% mutate_if(is.character,as.factor)
sick$Class<-sick$Class=="sick"
sick<-sick %>% mutate_if(is.logical,as.factor)

train_index<-suppressMessages(read_table2("indeksy_treningowe.txt"))
train_index<-train_index$y
train_sick<-sick[train_index,]
test_sick<-sick[-train_index,]
```

Because in mlr there is no AUPRC we create custom one using PRROC library.

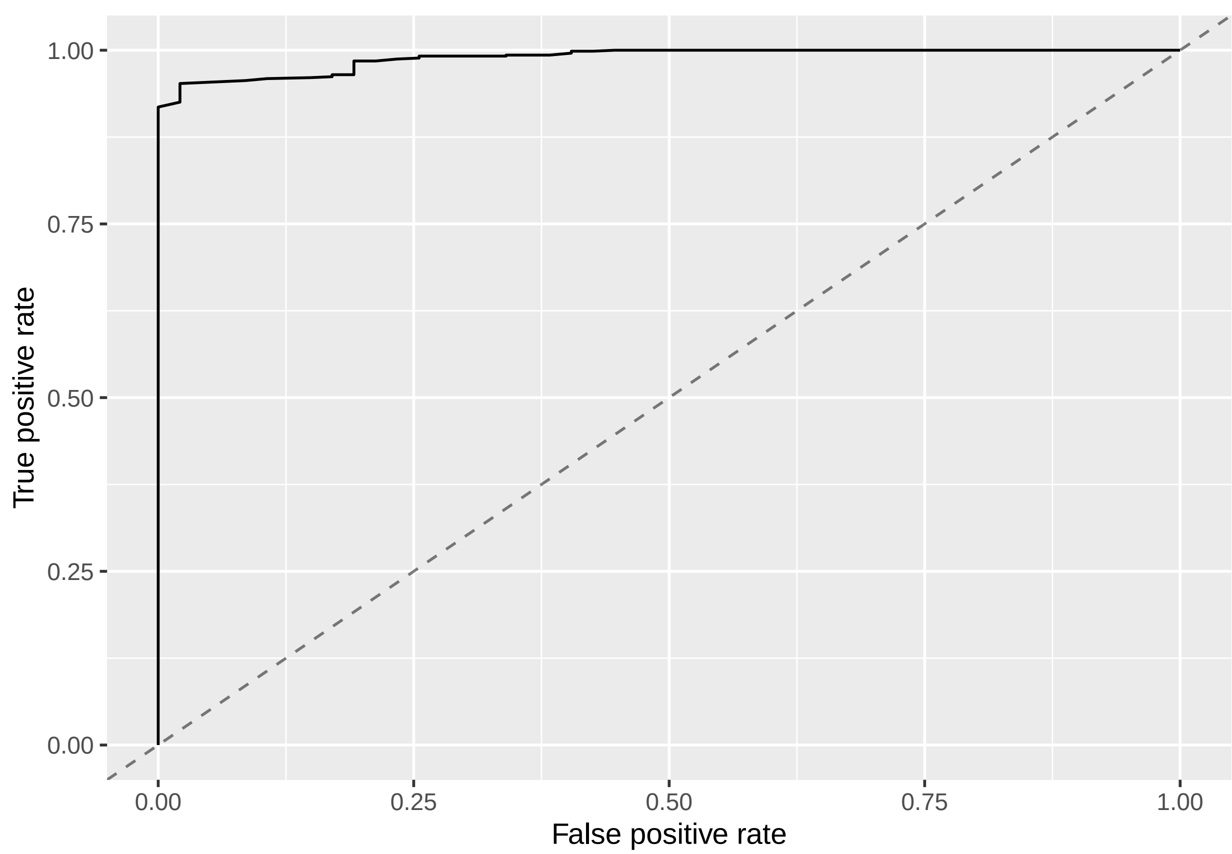
```
require(PRROC)
AUPRC2<-function(task, model, pred, feats, extra.args){
  fg<-pred$data[pred$data$truth=="TRUE",]$prob.TRUE
  bg<-pred$data[pred$data$truth=="FALSE",]$prob.TRUE
  pr <- pr.curve(scores.class0 = fg, scores.class1 = bg, curve = T)
```

```r
  pr$auc.integral
}
AUPRC<-makeMeasure(id = "auprc", minimize = FALSE,
                   properties = c("classif", "req.pred", "req.truth"),
                   best = 1, worst = 0, fun = AUPRC2)
```

In our dataset not only Class column is imbalanced, so we must consider dropping some columns out. Except hypopituitary because there is only 1 observation diffrent from the rest so we drop it right now.

cforest without further cleaning

```r
task<-makeClassifTask(data = train_sick, target = "Class")
rf_learner<-makeLearner("classif.cforest", predict.type = "prob")
rdesc = makeResampleDesc("CV", iters = 5)
r_rf = resample(rf_learner, task, rdesc, measures = list(mlr::auc, AUPRC),
                show.info = FALSE)

rf_model <- train(rf_learner, task)
prediction <- predict(rf_model, newdata = test_sick)

df = generateThreshVsPerfData(prediction, measures = list(fpr, tpr, mmce))
plotROCCurves(df)
```




```r
res_rf=mlr::performance(prediction,list(mlr::auc,AUPRC))
```

	score
auc.cross	0.990
auprc.cross	0.930
auc.test	0.989
auprc.test	0.882

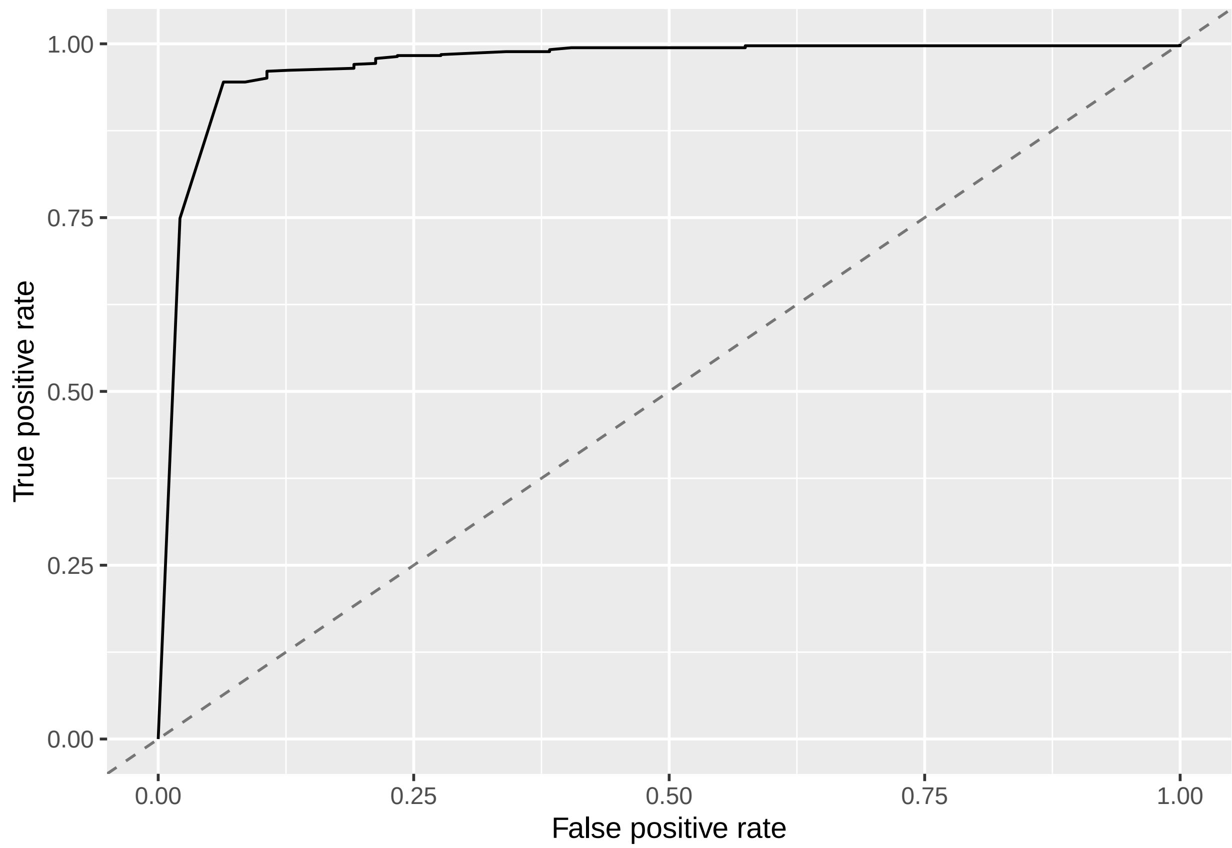
Cforest is very complex and slow model but gives us very good results. Our future models should try to be better than Cforest

gbm without further cleaning

```
task<-makeClassifTask(data = train_sick, target = "Class")
gbm_learner<-makeLearner("classif.gbm", predict.type = "prob")
rdesc = makeResampleDesc("CV", iters = 5)
r_gbm = resample(rf_learner, task, rdesc, measures = list(mlr::auc, AUPRC),
                show.info = FALSE)

gbm_model <- train(gbm_learner, task)
```

```
## Distribution not specified, assuming bernoulli ...
```

```
prediction <- predict(gbm_model, newdata = test_sick)

df = generateThreshVsPerfData(prediction, measures = list(fpr, tpr, mmce))
plotROCCurves(df)
```



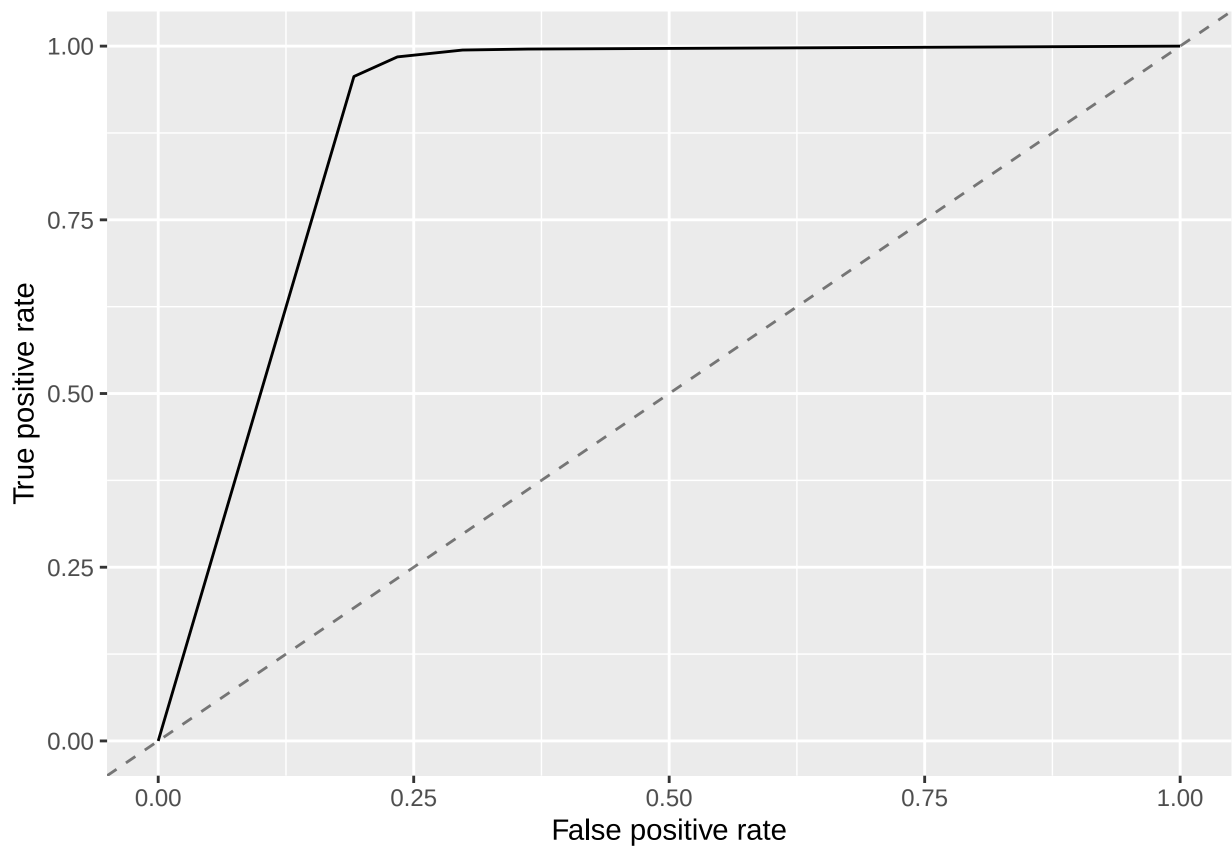
```
res_gbm=mlr::performance(prediction,list(mlr::auc,AUPRC))
```

	score
auc.cross	0.990
auprc.cross	0.924
auc.test	0.961
auprc.test	0.716

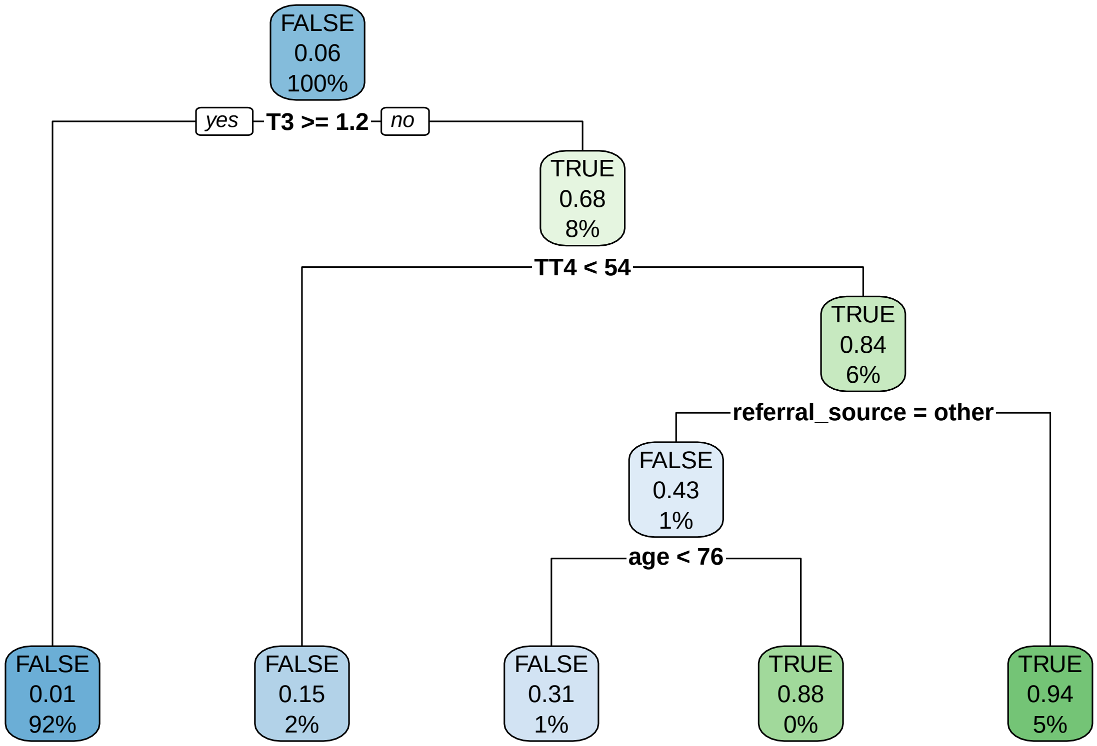
GBM turned out to be worse model than cforest, so in our aproach we are going to use cforest for predicting classes of generated dataset.

Rpart with 80% relevent columns

```
task<-makeClassifTask(data = train_sick, target = "Class")
rpart_learner<-makeLearner("classif.rpart", predict.type = "prob")
fv = generateFilterValuesData(task, method ="FSelectorRcpp_information.gain")
rdesc = makeResampleDesc("CV", iters = 5)
clean_task = filterFeatures(task, fval = fv, perc = 0.8)
r_rpart = resample(rpart_learner, clean_task, rdesc, measures = list(mlr::auc, AUPRC),
                   show.info = FALSE)
rpart_model <- train(rpart_learner, clean_task)
prediction <- predict(rpart_model, newdata = test_sick)
df = generateThreshVsPerfData(prediction, measures = list(fpr, tpr, mmce))
plotROCCurves(df)
```



```
res_rpart=mlr::performance(prediction,list(mlr::auc,AUPRC))

rpart.plot::rpart.plot(rpart_model$learner.model,roundint = FALSE)
```



	score
auc.cross	0.958
auprc.cross	0.855
auc.test	0.896
auprc.test	0.745

Results are not as good as Cforest but model iseft is very clear and simple.

Generating random dataset

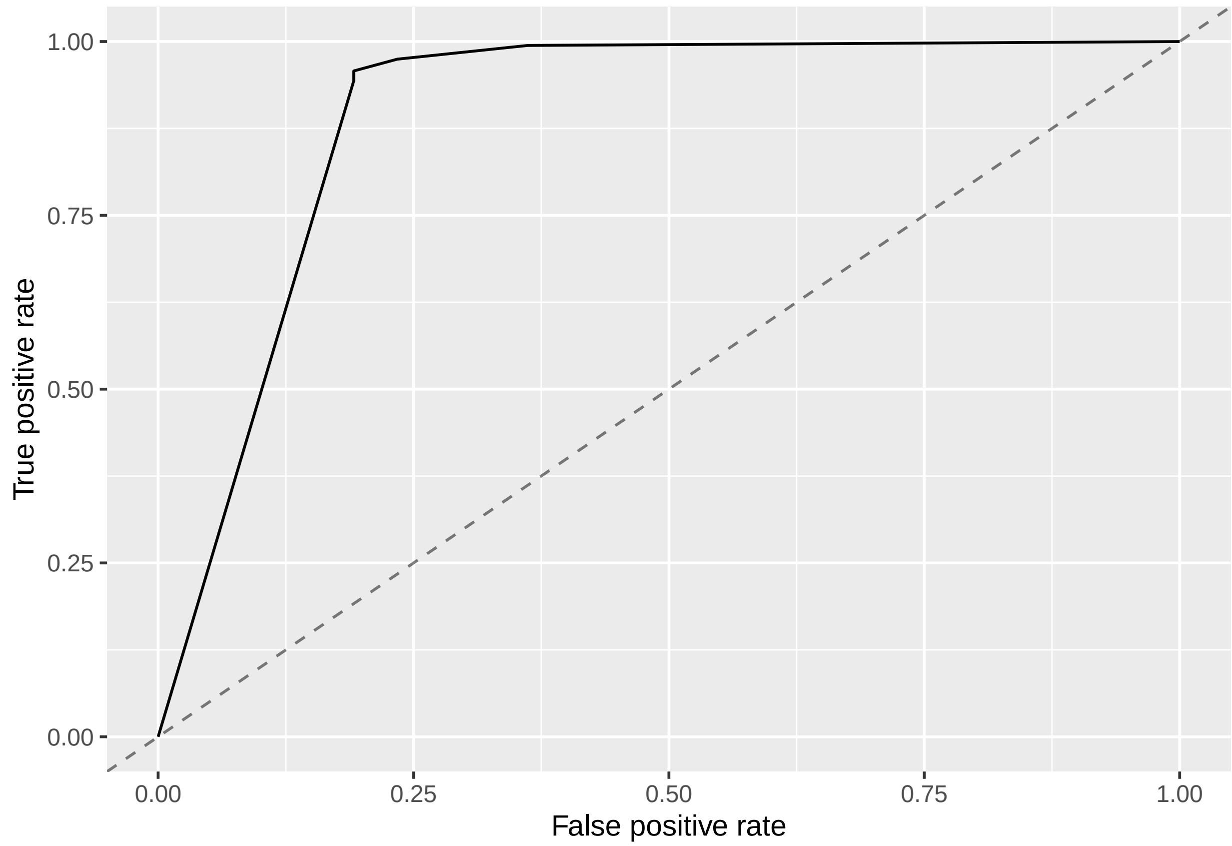
```
train_sick_t<-train_sick[train_sick$Class=="TRUE",]
train_sick_f<-train_sick[train_sick$Class=="FALSE",]

random_t<-sapply(1:27,FUN = function(x){train_sick_t[sample(1:184,4000,replace = TRUE),x]})

random_f<-sapply(1:27,FUN = function(x){train_sick_f[sample(1:2832,1000,replace = TRUE),x]})

random_t<-data.frame(random_t)

random_f<-data.frame(random_f)

prediction <- predict(rf_model,newdata =  random_t)
response_t<-prediction$data$response
certainty<-abs(prediction$data$prob.TRUE-0.5)*2
```

```
sure_t<-certainty>0.3

prediction <- predict(rf_model,newdata =  random_f)
response_f<-prediction$data$response
certainty<-abs(prediction$data$prob.TRUE-0.5)*2
sure_f<-certainty>0.3

random_t$Class<-response_t

random_f$Class<-response_f

random<-rbind(random_t[sure_t,],random_f[sure_f,])

random<-rbind(random,train_sick)
```

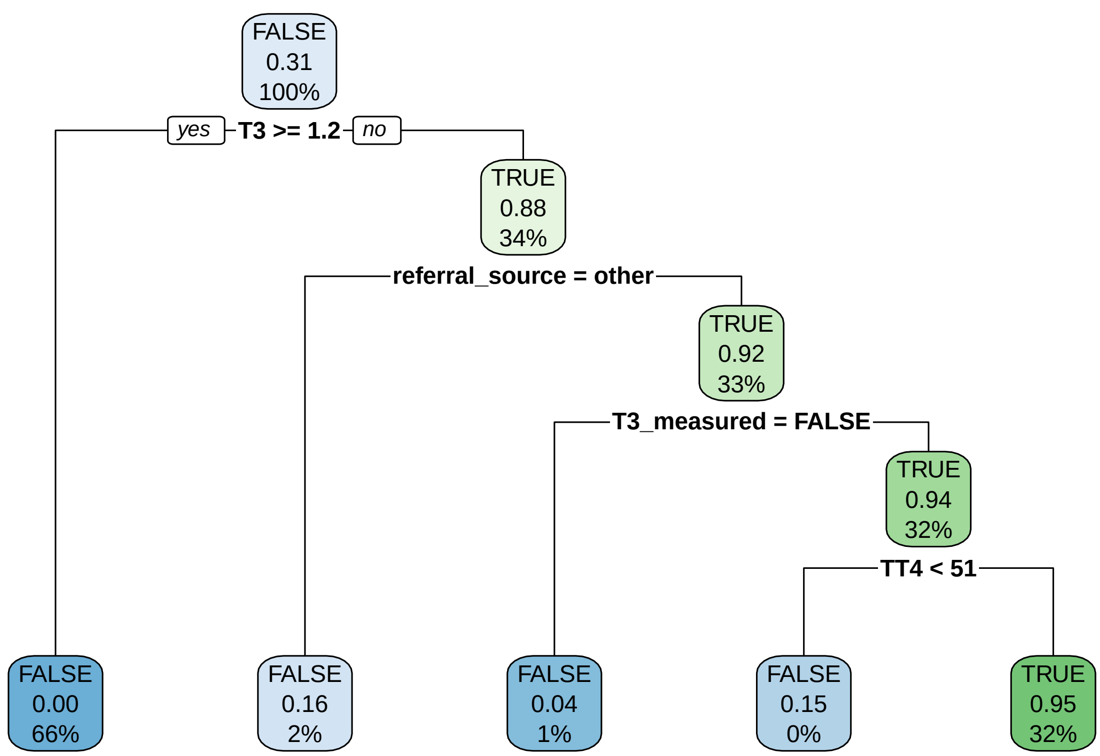
We generated additional data by splitting training dataset into parts with TRUE and FALSE classes then we generated random data in each part by resampling rows that means: for each column we were independently chosing random row and from such combination we got new observation. Classes of such obervations were determined by cforest we trained earlier. We also chose only such rows which cforest was certain of (probablity greater than 65%).

Rpart with generated dataset

```
task<-makeClassifTask(data = random, target = "Class")
rpart_learner<-makeLearner("classif.rpart", predict.type = "prob")
rdesc = makeResampleDesc("CV", iters = 5)
r_rpart_random = resample(rpart_learner, task, rdesc, measures = list(mlr::auc, AUPRC),show.info = FALS

rpart_model <- train(rpart_learner, task)
prediction <- predict(rpart_model, newdata = test_sick)

df = generateThreshVsPerfData(prediction, measures = list(fpr, tpr, mmce))
plotROCCurves(df)
```




```r
res_rpart_random=mlr::performance(prediction,list(mlr::auc,AUPRC))

rpart.plot::rpart.plot(rpart_model$learner.model,roundint = FALSE)
```



	score
auc.cross	0.984
auprc.cross	0.943
auc.test	0.894
auprc.test	0.712

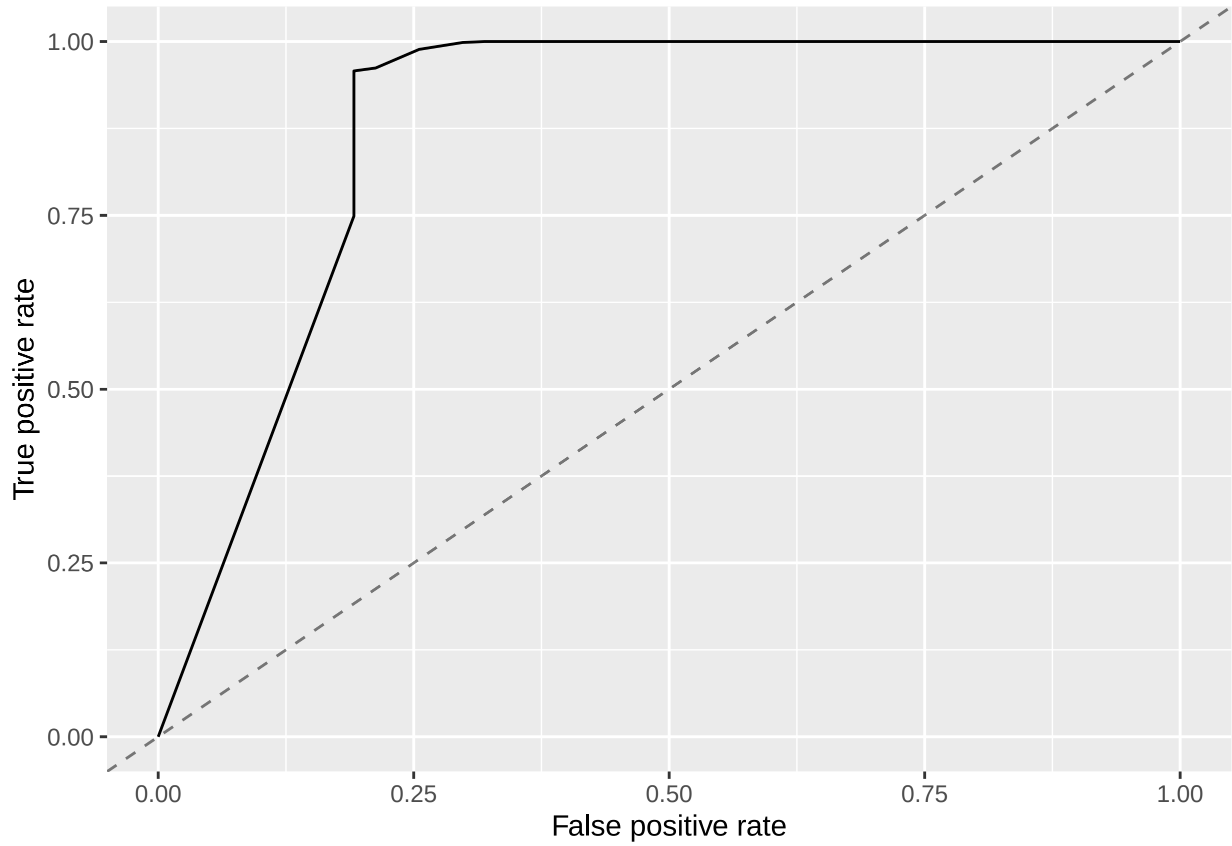
Unfortunately we got worse model.

Rpart tuned

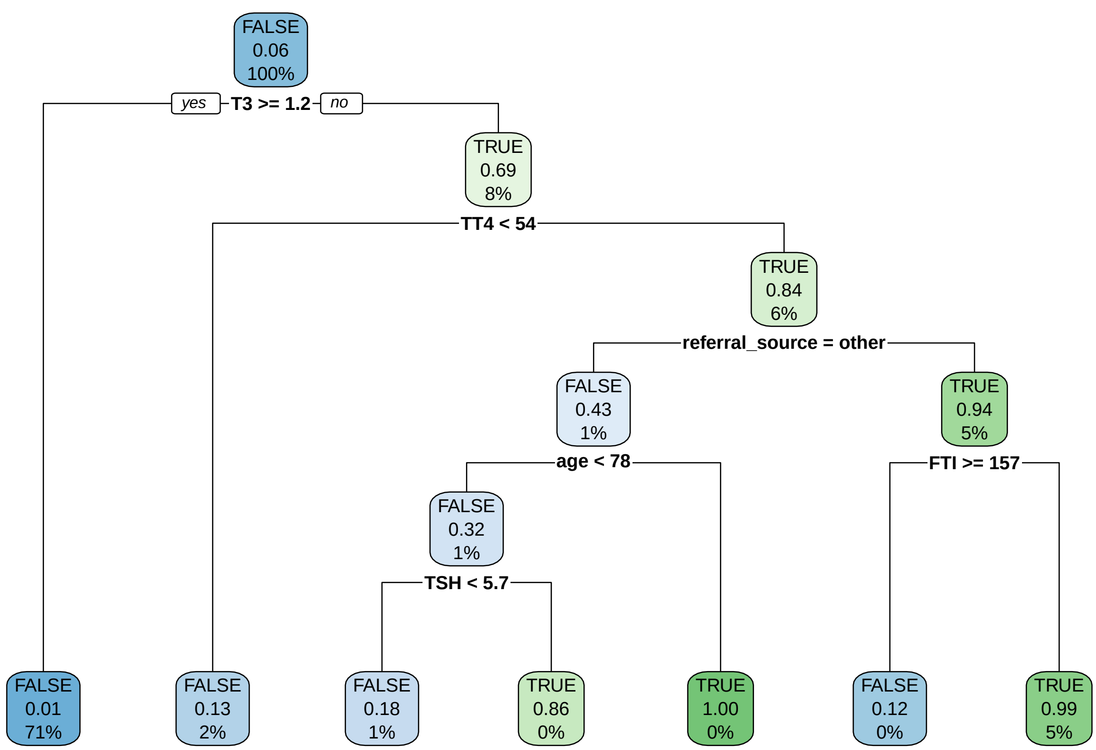
```
learner<-makeLearner("classif.rpart", predict.type = "prob")
task<-makeClassifTask(data = train_sick, target = "Class")

dt_param <- makeParamSet(
  makeDiscreteParam("minsplit", values=seq(5,10,1)),
  makeDiscreteParam("minbucket", values=seq(round(5/3,0), round(10/3,0), 1)),
  makeNumericParam("cp", lower = 0.01, upper = 0.05),
  makeDiscreteParam("maxcompete", values=6),
  makeDiscreteParam("usesurrogate", values=0),
  makeDiscreteParam("maxdepth", values=5) )

ctrl = makeTuneControlGrid()
rdesc = makeResampleDesc("CV", iters = 5L, stratify=TRUE)
(dt_tuneparam <- tuneParams(learner=learner,
                            resampling=rdesc,
                            measures=list(AUPRC,mlr::acc),
                            par.set=dt_param,
                            control=ctrl,
                            task=task,
                            show.info = FALSE) )
```

```
## Tune result:
## Op. pars: minsplit=5; minbucket=2; cp=0.0233; maxcompete=6; usesurrogate=0; maxdepth=5
## auprc.test.mean=0.8267135,acc.test.mean=0.9854096
```

```
dtree <- setHyperPars(learner, par.vals = dt_tuneparam$x)

rdesc = makeResampleDesc("CV", iters = 5)
r_rpart_tuned = resample(dtree, task, rdesc, measures = list(mlr::auc, AUPRC),show.info = FALSE)

dtree_train <- train(learner=dtree, task=task)
prediction <- predict(dtree_train, newdata = test_sick)

df = generateThreshVsPerfData(prediction, measures = list(fpr, tpr, mmce))
plotROCCurves(df)
```




```
res_rpart_tuned=mlr::performance(prediction,list(mlr::auc,AUPRC))

rpart.plot::rpart.plot(dtree_train$learner.model,roundint = FALSE)
```



	score
auc.cross	0.951
auprc.cross	0.820
auc.test	0.878
auprc.test	0.799

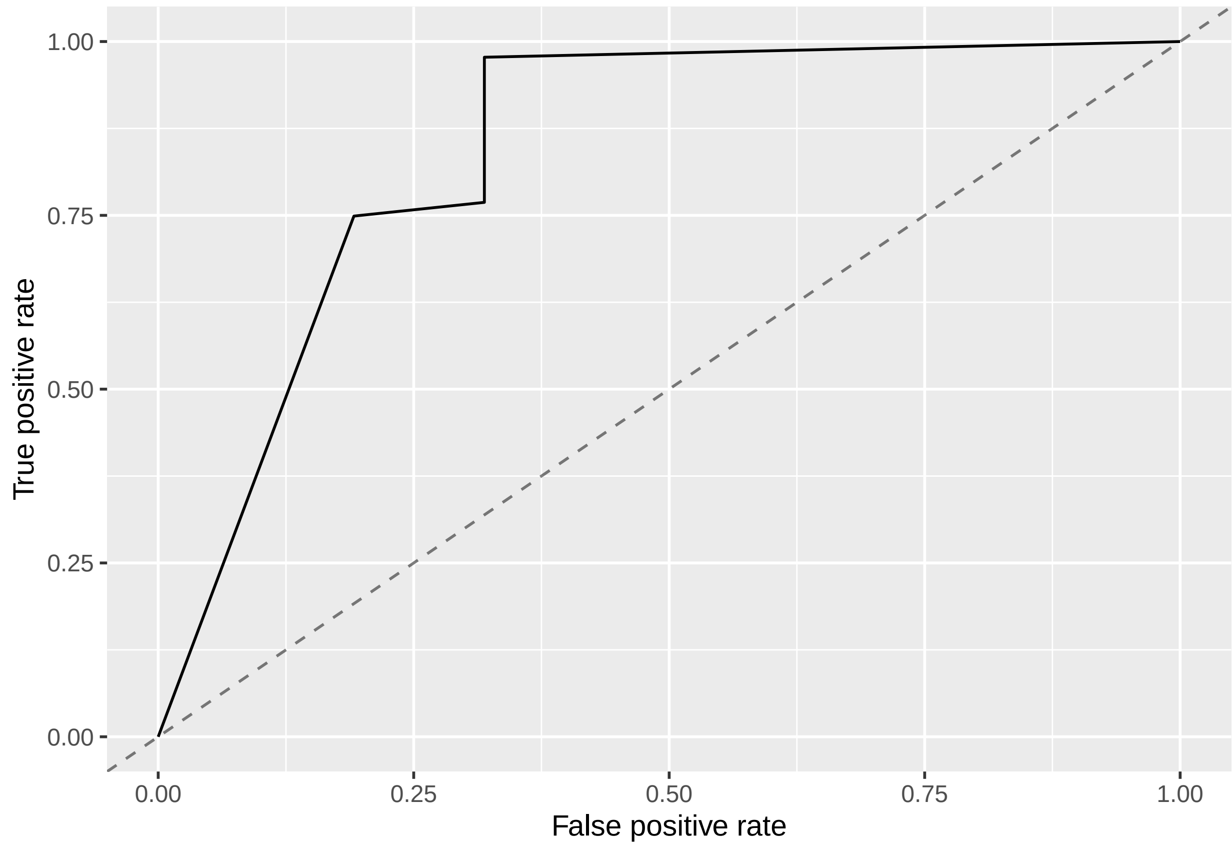
Model after tuning performs a bit better than earlier, but is also more complicated.

Rpart tuned with generated dataset

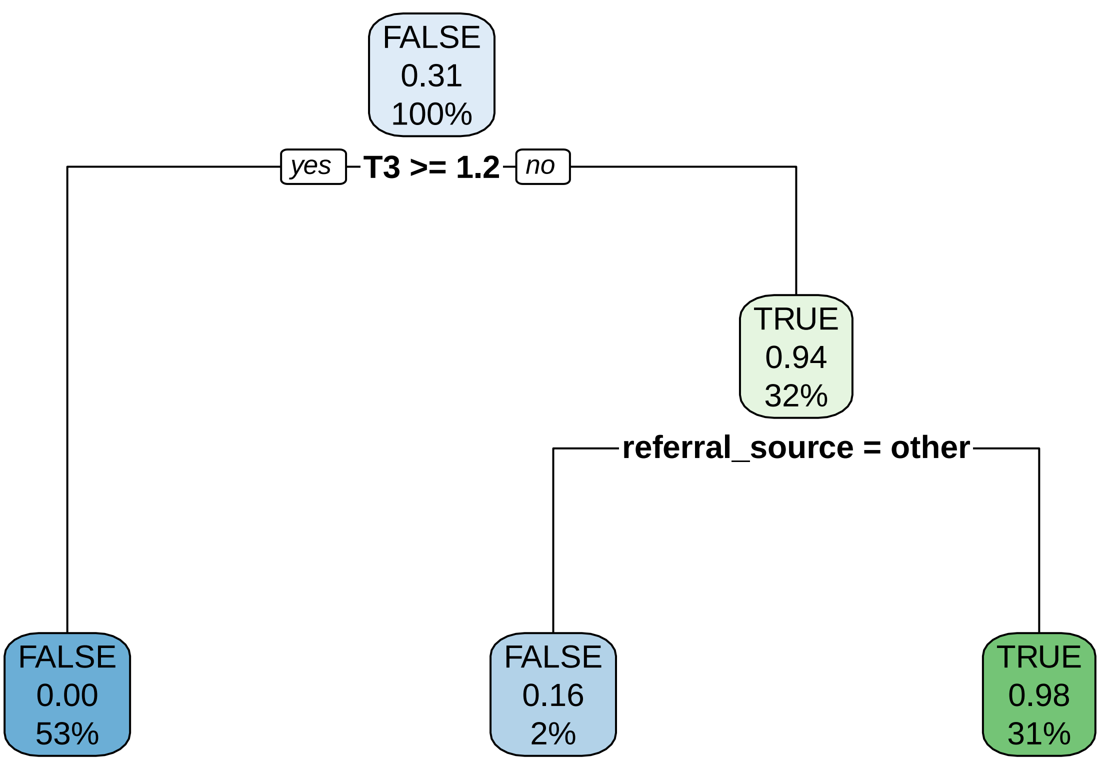
```
learner<-makeLearner("classif.rpart", predict.type = "prob")
task<-makeClassifTask(data = random, target = "Class")

dt_param <- makeParamSet(
  makeDiscreteParam("minsplit", values=seq(5,10,1)),
  makeDiscreteParam("minbucket", values=seq(round(5/3,0), round(10/3,0), 1)),
  makeNumericParam("cp", lower = 0.01, upper = 0.05),
  makeDiscreteParam("maxcompete", values=6),
  makeDiscreteParam("usesurrogate", values=0),
  makeDiscreteParam("maxdepth", values=5) )

ctrl = makeTuneControlGrid()
rdesc = makeResampleDesc("CV", iters = 5L, stratify=TRUE)
(dt_tuneparam <- tuneParams(learner=learner,
                           resampling=rdesc,
                           measures=list(AUPRC,mlr::acc),
                           par.set=dt_param,
                           control=ctrl,
                           task=task,
                           show.info = FALSE) )
```

```
## Tune result:
## Op. pars: minsplit=10; minbucket=3; cp=0.01; maxcompete=6; usesurrogate=0; maxdepth=5
## auprc.test.mean=0.9767325,acc.test.mean=0.9896050
```

```
dtree <- setHyperPars(learner, par.vals = dt_tuneparam$x)

rdesc = makeResampleDesc("CV", iters = 5)
r_rpart_random_tuned = resample(dtree, task, rdesc, measures = list(mlr::auc, AUPRC),show.info = FALSE)

dtree_train <- train(learner=dtree, task=task)
prediction <- predict(dtree_train, newdata = test_sick)

df = generateThreshVsPerfData(prediction, measures = list(fpr, tpr, mmce))
plotROCCurves(df)
```




```
res_rpart_random_tuned=mlr::performance(prediction,list(mlr::auc,AUPRC))

rpart.plot::rpart.plot(dtree_train$learner.model,roundint = FALSE)
```

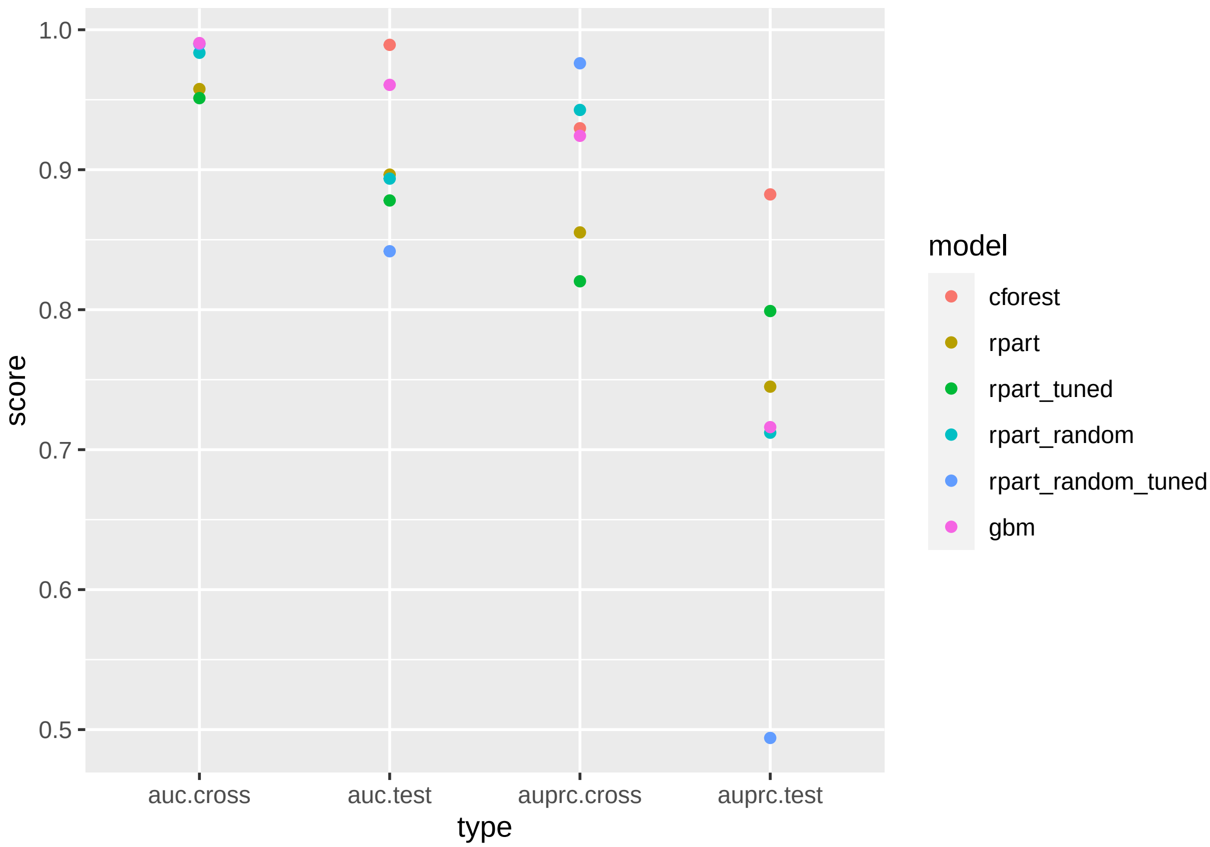


	score
auc.cross	0.990
auprc.cross	0.976
auc.test	0.842
auprc.test	0.494

Model overfitted very badly.

Summary

```
ggplot(all_score,aes(x=type,y=score,color=model))+geom_point()
```



Analizing this plot we can observe many interesting things. First of all our aproach with randomly generated data did not work. During cross validation on training data set it was getting similiar results to the cforest, but on test dataset it was getting worse results. This aproach may require more experiments and theoretical knowledge on how to prevent overfitting. Our tuned rpart was always bit worse during cross validation than default rpart, but on test dataset it was getting much better results in AUPRC and sligthy better AUC.