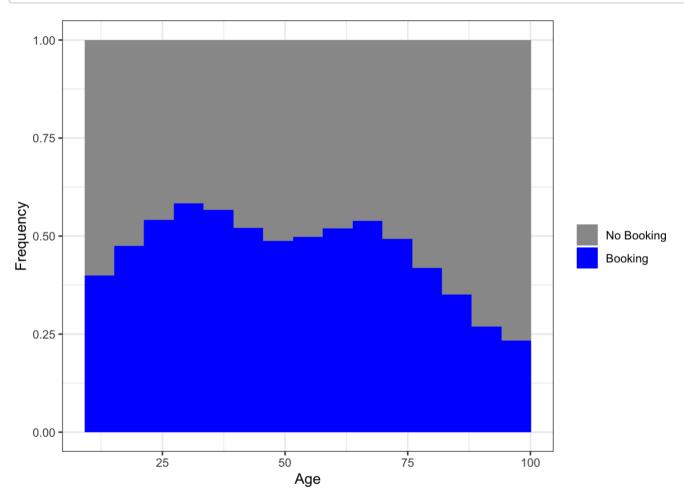
Booking predictions

The best team 30/11/2019

Preprocessing

```
# Read and pre-porocess the datasets
users train <- read.csv("full train.csv")</pre>
users test <- read.csv("full test.csv")</pre>
users train$signup flow = factor(users train$signup flow)
users_test$signup_flow = factor(users_test$signup_flow)
users train$booking = factor(users train$booking)
users test$booking = factor(users test$booking)
users train trip <- users train %>% select(-c("id", "date first booking", "country des
tination"))
users_test_trip = users_test %>% select(-c("id","date_first_booking", "country_desti
nation"))
users train trip <- na.omit(users train trip)</pre>
users test trip <- na.omit(users test trip)</pre>
#this is needed to equalize the levels between training and testing sets so we can do
predictions
levels(users test trip$gender) <- levels(users train trip$gender)</pre>
levels(users test trip$signup method) <- levels(users train trip$signup method)</pre>
levels(users_test_trip$signup_flow) <- levels(users_train_trip$signup_flow)</pre>
levels(users test trip$language) <- levels(users train trip$language)</pre>
levels(users test trip$affiliate channel) <- levels(users train trip$affiliate channe
1)
levels(users_test_trip$affiliate_provider) <- levels(users_train_trip$affiliate_provi</pre>
levels(users test trip$first affiliate tracked) <- levels(users train trip$first affi</pre>
liate tracked)
levels(users_test_trip$signup_app) <- levels(users_train_trip$signup_app)</pre>
levels(users test trip$first device type) <- levels(users train trip$first device typ
levels(users test trip$first browser) <- levels(users train trip$first browser)</pre>
levels(users_test_trip$age_generation) <- levels(users_train_trip$age_generation)</pre>
levels(users test trip$age quantil) <- levels(users train trip$age quantil)</pre>
levels(users test trip$millenials) <- levels(users train trip$millenials)</pre>
levels(users test trip$device type colapsed) <- levels(users train trip$device type c
olapsed)
get stats <- function (predictions, true data) {</pre>
  matrix = table(true data, predictions)
  accuracy = (matrix[1,1]+matrix[2,2])/length(true data)
  TPR = (matrix[2,2])/sum(matrix[2,])
 FPR = (matrix[1,2])/sum(matrix[1,])
  return(c(accuracy, TPR, FPR))
}
get auc <- function(predicted probabilities, true data) {</pre>
  rocr.pred.rf <- prediction(predicted probabilities, true data)</pre>
  performance(rocr.pred.rf, "auc")@y.values[[1]]
}
```

```
library(ggplot2)
ggplot(data=users_train) +
  geom_histogram(aes(x=age,fill=(booking==1)),position='fill', bins = 15) +
  theme_bw() +
  xlab('Age') +
  ylab('Frequency') +
  scale_fill_manual (name='', labels=c('No Booking','Booking'), values=c('grey60','blue'))
```



Random Forest

```
# control <- trainControl(method="repeatedcv", number=5, repeats=1, search="random")</pre>
#
# train.rf.oob <- train(booking ~ .,</pre>
                         data = users train trip,
                         method="rf",
                         tuneGrid=data.frame(mtry=1:sqrt(ncol(users_train_trip))),
                         nodesize = 25,
                         ntree = 100,
                         trControl=control)
# mtry chosen <- train.rf.oob$bestTune[[1]]</pre>
### mtry chosen after cv = 4
mtry_chosen <- 4
model RF = randomForest(booking ~ . ,
                                    data = users train trip,
                                    ntree = 500,
                                   mtry = mtry_chosen,
                                   nodesize = 25,
                                   na.action=na.exclude)
importance.rf <- data.frame(imp=importance(model RF))</pre>
importance.rf
```

	MeanDecreaseGini <dbl></dbl>
gender	713.09795
age	1435.98847
signup_method	2727.67816
signup_flow	638.49527
language	445.69879
affiliate_channel	799.80260
affiliate_provider	557.67241
first_affiliate_tracked	604.78668
signup_app	190.79557
first_device_type	458.29991
1-10 of 18 rows	Previous 1 2 Next

Prediction and evaluation

```
#predicting binary outcomes directly
pred_RF = predict(model_RF, newdata = users_test_trip)
```

```
#confusion matrix
table(pred_RF, users_test_trip$booking)
```

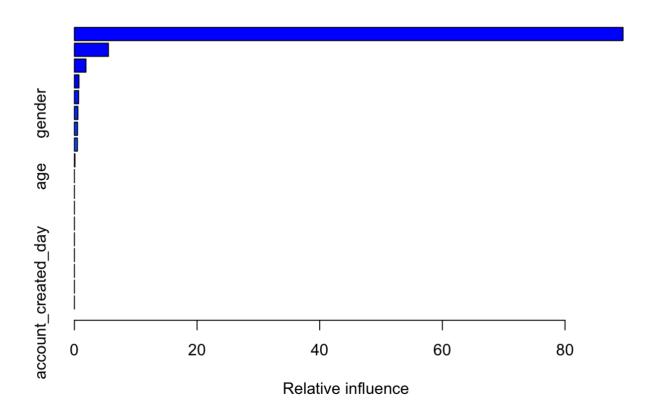
```
get_stats(pred_RF, users_test_trip$booking)
```

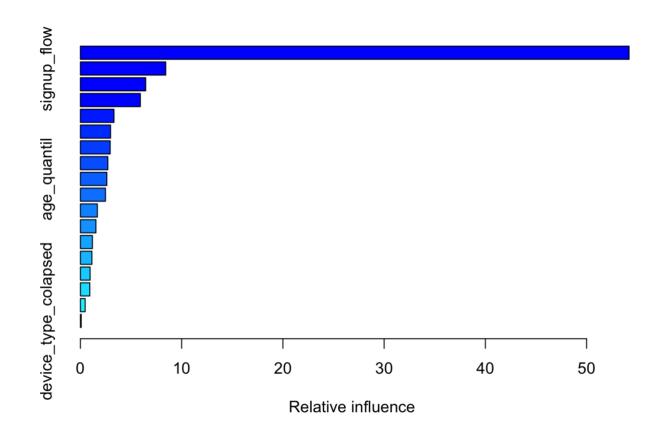
```
## [1] 0.6321228 0.7173198 0.4727808
```

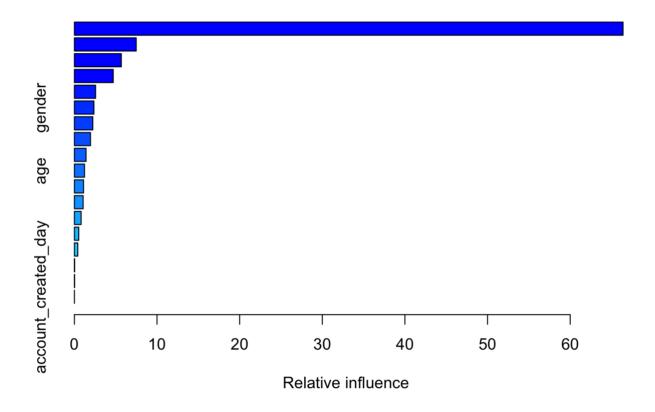
```
#to get AUC, we need to predict probabilities instead
get_auc(predict(model_RF, newdata = users_test_trip, type = "prob")[, 2], users_test_
trip$booking)
```

```
## [1] 0.663925
```

Boosting







Prediction and evaluation

```
pred_GBM_1_prob <- predict(model_GBM_1, newdata = users_test_trip, n.trees = 100, ty
pe = "response")
pred_GBM_1 <- as.numeric(pred_GBM_1_prob[, 2, 1] <= pred_GBM_1_prob[, 1, 1])

pred_GBM_2_prob <- predict(model_GBM_2, newdata = users_test_trip, n.trees = 500, ty
pe = "response")
pred_GBM_2 <- as.numeric(pred_GBM_2_prob[, 2, 1] <= pred_GBM_2_prob[, 1, 1])

pred_GBM_3_prob <- predict(model_GBM_3, newdata = users_test_trip, n.trees = 1000, t
ype = "response")
pred_GBM_3 <- as.numeric(pred_GBM_3_prob[, 2, 1] <= pred_GBM_3_prob[, 1, 1])</pre>
```

```
get_stats(pred_GBM_1, users_test_trip$booking)
```

```
## [1] 0.3662265 0.3434640 0.6057459
```

```
get_auc(pred_GBM_1_prob[, 2, ], users_test_trip$booking)
```

```
## [1] 0.6632239
```

```
get_stats(pred_GBM_2, users_test_trip$booking)
```

```
## [1] 0.4074282 0.5504637 0.7686924
```

get_auc(pred_GBM_2_prob[, 2,], users_test_trip\$booking)

[1] 0.6724686

get_stats(pred_GBM_3, users_test_trip\$booking)

[1] 0.3659624 0.3539336 0.6192265

get_auc(pred_GBM_3_prob[, 2,], users_test_trip\$booking)

[1] 0.6713134