

Titanic : Machine Learning from disaster

Introduction

The objective of this project was to complete the analysis of what sorts of people were likely to survive. In particular , the kaggle competition ask's you to apply the tools of machine learning to predict which passengers survived the tragedy.

First prediction

My first analysis was studing the structure of data and to find out how many passangers have survived and how many have passed away. The table command helped me explore if a variable has any predictive value. The variables that had influence on the survival rate were gender and age. Using these variables i made a simple prediction on the test dataset.

```
# Structure of training and test set  
str(train)
```

```
## 'data.frame':   891 obs. of  12 variables:  
## $ PassengerId: int   1 2 3 4 5 6 7 8 9 10 ...  
## $ Survived   : int   0 1 1 1 0 0 0 0 1 1 ...  
## $ Pclass     : int   3 1 3 1 3 3 1 3 3 2 ...  
## $ Name       : Factor w/ 891 levels "Abbing, Mr. Anthony",...: 109 191 358 277 16 559 520 629 416 58...  
## $ Sex        : Factor w/ 2 levels "female","male": 2 1 1 1 2 2 2 2 1 1 ...  
## $ Age        : num   22 38 26 35 35 NA 54 2 27 14 ...  
## $ SibSp      : int   1 1 0 1 0 0 0 3 0 1 ...  
## $ Parch      : int   0 0 0 0 0 0 0 1 2 0 ...  
## $ Ticket     : Factor w/ 681 levels "110152","110413",...: 525 596 662 50 473 276 86 396 345 133 ...  
## $ Fare       : num    7.25 71.28 7.92 53.1 8.05 ...  
## $ Cabin      : Factor w/ 148 levels "", "A10", "A14",...: 1 83 1 57 1 1 131 1 1 1 ...  
## $ Embarked   : Factor w/ 4 levels "", "C", "Q", "S": 4 2 4 4 4 3 4 4 2 ...
```

```
str(test)
```

```
## 'data.frame':   418 obs. of  11 variables:  
## $ PassengerId: int  892 893 894 895 896 897 898 899 900 901 ...  
## $ Pclass     : int   3 3 2 3 3 3 3 2 3 3 ...  
## $ Name       : Factor w/ 418 levels "Abbott, Master. Eugene Joseph",...: 210 409 273 414 182 370 85 ...  
## $ Sex        : Factor w/ 2 levels "female","male": 2 1 2 2 1 2 1 2 1 2 ...  
## $ Age        : num   34.5 47 62 27 22 14 30 26 18 21 ...  
## $ SibSp      : int   0 1 0 0 1 0 0 1 0 2 ...  
## $ Parch      : int   0 0 0 0 1 0 0 1 0 0 ...  
## $ Ticket     : Factor w/ 363 levels "110469","110489",...: 153 222 74 148 139 262 159 85 101 268 ...  
## $ Fare       : num    7.83 7 9.69 8.66 12.29 ...  
## $ Cabin      : Factor w/ 77 levels "", "A11", "A18",...: 1 1 1 1 1 1 1 1 1 1 ...  
## $ Embarked   : Factor w/ 3 levels "C","Q","S": 2 3 2 3 3 3 2 3 1 3 ...
```

```
# Passengers that survived vs passengers that passed away
```

```
table(train$Survived)
```

```
##
##    0    1
## 549 342
```

```
prop.table(table(train$Survived))
```

```
##
##           0           1
## 0.6161616 0.3838384
```

```
# Males & females that survived vs males & females that passed away
table(train$Sex, train$Survived)
```

```
##
##           0    1
## female  81 233
## male   468 109
```

```
prop.table(table(train$Sex, train$Survived), 1)
```

```
##
##           0           1
## female 0.2579618 0.7420382
## male   0.8110919 0.1889081
```

```
# Create the column child, and indicate whether child or no child
train$Child <- NA
train$Child[train$Age < 18] <- 1
train$Child[train$Age >= 18] <- 0
```

```
# Two-way comparison
table(train$Child, train$Survived)
```

```
##
##           0    1
## 0 372 229
## 1  52  61
```

```
prop.table(table(train$Child, train$Survived), 1)
```

```
##
##           0           1
## 0 0.6189684 0.3810316
## 1 0.4601770 0.5398230
```

```
# Prediction based on gender
test_one <- test
test_one$Survived <- NA
test_one$Survived[test_one$Sex == 'female'] <- 1
test_one$Survived[test_one$Sex == 'male'] <- 0
```

Prediction using Decision tree

Created a decision tree using rpart function and discovered variables that play an important role whether or not a passenger will survive. Made prediction using the test set and got a result that outperforms a solution using purely gender. To improve the model, manipulated the cp and minisplit in the decision tree.

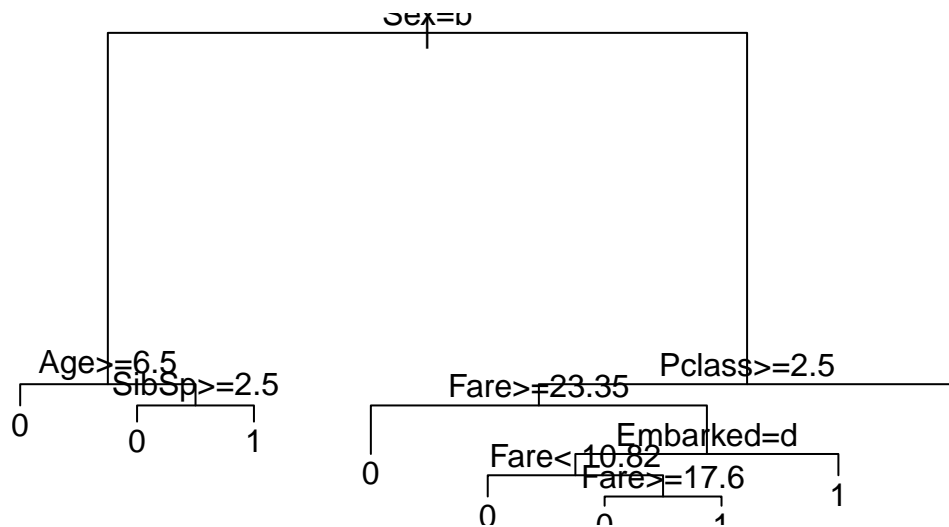
cp - determines when the splitting up of the decision tree stops.

minsplit - determines the minimum amount of observations in a leaf of the tree.

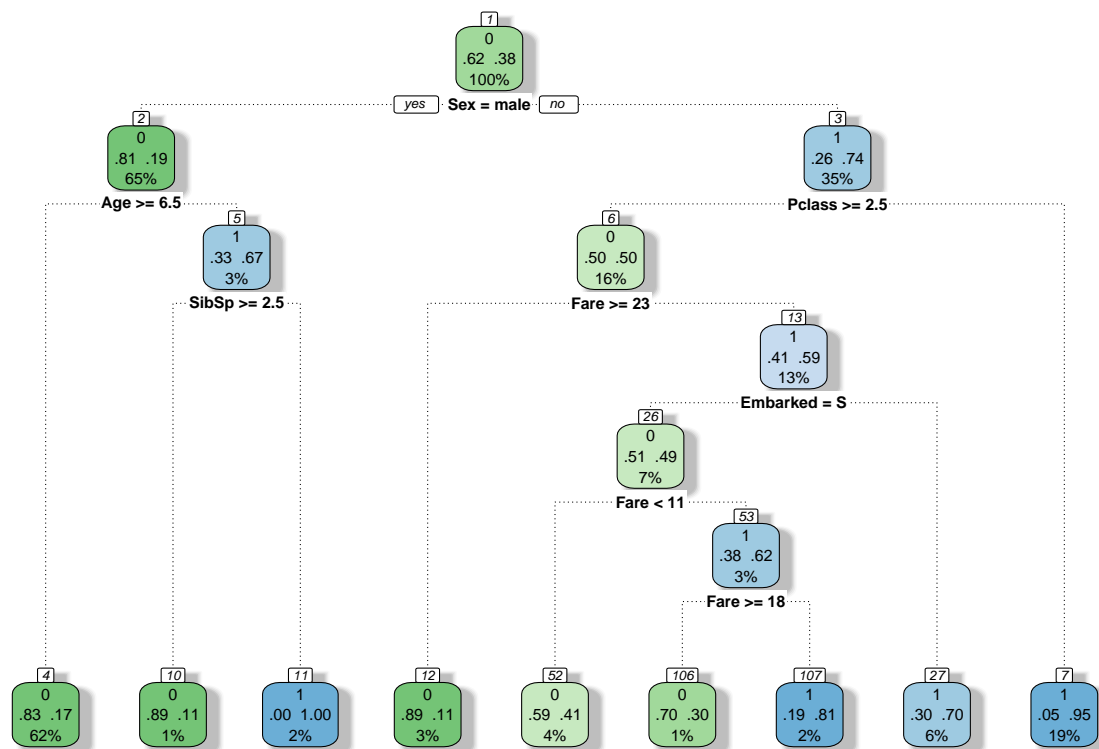
The model generalizes well compared to previous one.

```
# Build the decision tree
my_tree_two <- rpart(Survived ~ Pclass + Sex + Age + SibSp + Parch + Fare + Embarked,
                     data = train, method = "class")

# Visualize the decision tree
plot(my_tree_two)
text(my_tree_two)
```



```
# Plot the tree
fancyRpartPlot(my_tree_two)
```



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```
# Make prediction using the test set
my_prediction <- predict(my_tree_two, test, type="class")

# Create a data frame with two columns: PassengerId & Survived. Survived contains predictions
my_solution <- data.frame(PassengerId = test$PassengerId , Survived = my_prediction)

# Check that data frame has 418 entries
nrow(my_solution) == 418

## [1] TRUE

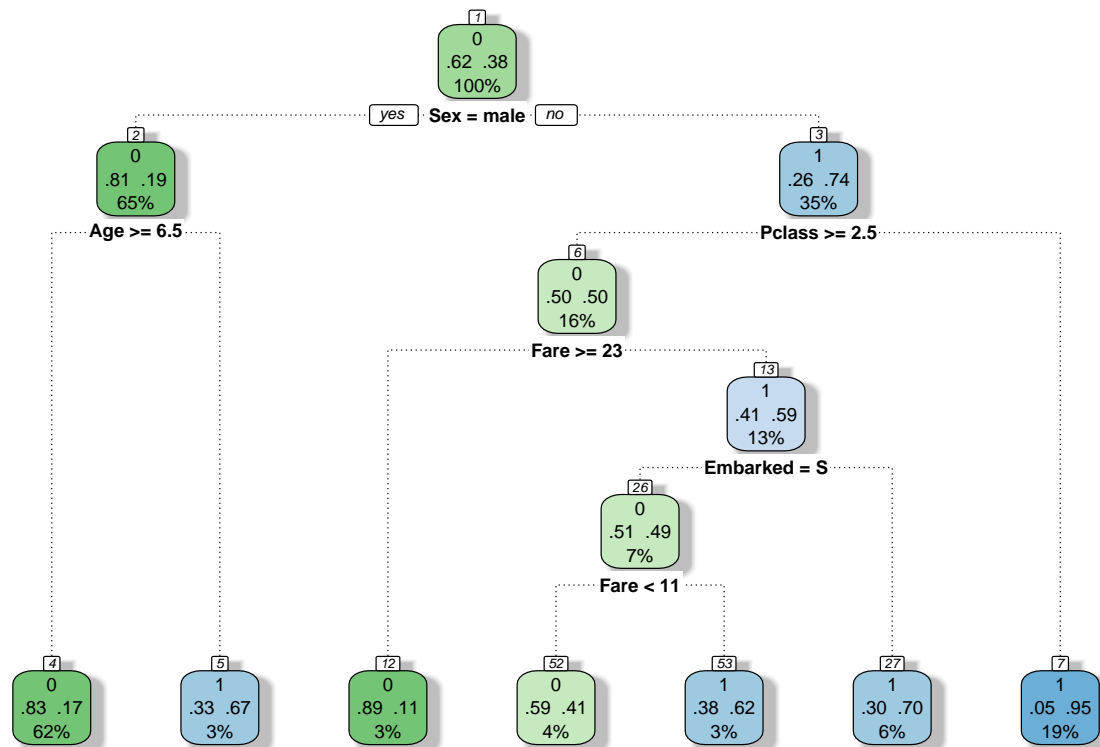
# Write solution to a csv file with the name my_solution.csv
write.csv(my_solution, file = 'my_solution.csv', row.names = FALSE)

# Create a new decision tree
my_tree_three <- rpart(Survived ~ Pclass + Sex + Age + SibSp + Parch + Fare + Embarked,
  data = train, method = "class", control = rpart.control(minsplit = 50, cp = 0),
  rpart.control(cp = 0, minsplit = 50)

## $minsplit
## [1] 50
##
## $minbucket
## [1] 17
##
## $cp
## [1] 0
```

```
##
## $maxcompete
## [1] 4
##
## $maxsurrogate
## [1] 5
##
## $usesurrogate
## [1] 2
##
## $surrogatestyle
## [1] 0
##
## $maxdepth
## [1] 30
##
## $xval
## [1] 10
```

```
# Visualize new decision tree
fancyRpartPlot(my_tree_three)
```



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```
# View my_solution
my_solution
```

```
## PassengerId Survived
## 1 892 0
```

## 2	893	0
## 3	894	0
## 4	895	0
## 5	896	1
## 6	897	0
## 7	898	1
## 8	899	0
## 9	900	1
## 10	901	0
## 11	902	0
## 12	903	0
## 13	904	1
## 14	905	0
## 15	906	1
## 16	907	1
## 17	908	0
## 18	909	0
## 19	910	0
## 20	911	1
## 21	912	0
## 22	913	0
## 23	914	1
## 24	915	0
## 25	916	1
## 26	917	0
## 27	918	1
## 28	919	0
## 29	920	0
## 30	921	0
## 31	922	0
## 32	923	0
## 33	924	0
## 34	925	0
## 35	926	0
## 36	927	0
## 37	928	0
## 38	929	0
## 39	930	0
## 40	931	0
## 41	932	0
## 42	933	0
## 43	934	0
## 44	935	1
## 45	936	1
## 46	937	0
## 47	938	0
## 48	939	0
## 49	940	1
## 50	941	1
## 51	942	0
## 52	943	0
## 53	944	1
## 54	945	1
## 55	946	0

## 56	947	0
## 57	948	0
## 58	949	0
## 59	950	0
## 60	951	1
## 61	952	0
## 62	953	0
## 63	954	0
## 64	955	1
## 65	956	0
## 66	957	1
## 67	958	1
## 68	959	0
## 69	960	0
## 70	961	1
## 71	962	1
## 72	963	0
## 73	964	0
## 74	965	0
## 75	966	1
## 76	967	0
## 77	968	0
## 78	969	1
## 79	970	0
## 80	971	1
## 81	972	1
## 82	973	0
## 83	974	0
## 84	975	0
## 85	976	0
## 86	977	0
## 87	978	1
## 88	979	0
## 89	980	1
## 90	981	1
## 91	982	1
## 92	983	0
## 93	984	1
## 94	985	0
## 95	986	0
## 96	987	0
## 97	988	1
## 98	989	0
## 99	990	0
## 100	991	0
## 101	992	1
## 102	993	0
## 103	994	0
## 104	995	0
## 105	996	1
## 106	997	0
## 107	998	0
## 108	999	0
## 109	1000	0

## 110	1001	0
## 111	1002	0
## 112	1003	1
## 113	1004	1
## 114	1005	1
## 115	1006	1
## 116	1007	0
## 117	1008	0
## 118	1009	1
## 119	1010	0
## 120	1011	1
## 121	1012	1
## 122	1013	0
## 123	1014	1
## 124	1015	0
## 125	1016	0
## 126	1017	1
## 127	1018	0
## 128	1019	1
## 129	1020	0
## 130	1021	0
## 131	1022	0
## 132	1023	0
## 133	1024	0
## 134	1025	0
## 135	1026	0
## 136	1027	0
## 137	1028	0
## 138	1029	0
## 139	1030	0
## 140	1031	0
## 141	1032	0
## 142	1033	1
## 143	1034	0
## 144	1035	0
## 145	1036	0
## 146	1037	0
## 147	1038	0
## 148	1039	0
## 149	1040	0
## 150	1041	0
## 151	1042	1
## 152	1043	0
## 153	1044	0
## 154	1045	1
## 155	1046	0
## 156	1047	0
## 157	1048	1
## 158	1049	0
## 159	1050	0
## 160	1051	1
## 161	1052	1
## 162	1053	0
## 163	1054	1

## 164	1055	0
## 165	1056	0
## 166	1057	0
## 167	1058	0
## 168	1059	0
## 169	1060	1
## 170	1061	0
## 171	1062	0
## 172	1063	0
## 173	1064	0
## 174	1065	0
## 175	1066	0
## 176	1067	1
## 177	1068	1
## 178	1069	0
## 179	1070	1
## 180	1071	1
## 181	1072	0
## 182	1073	0
## 183	1074	1
## 184	1075	0
## 185	1076	1
## 186	1077	0
## 187	1078	1
## 188	1079	0
## 189	1080	0
## 190	1081	0
## 191	1082	0
## 192	1083	0
## 193	1084	0
## 194	1085	0
## 195	1086	0
## 196	1087	0
## 197	1088	1
## 198	1089	0
## 199	1090	0
## 200	1091	0
## 201	1092	1
## 202	1093	1
## 203	1094	0
## 204	1095	1
## 205	1096	0
## 206	1097	0
## 207	1098	1
## 208	1099	0
## 209	1100	1
## 210	1101	0
## 211	1102	0
## 212	1103	0
## 213	1104	0
## 214	1105	1
## 215	1106	0
## 216	1107	0
## 217	1108	1

## 218	1109	0
## 219	1110	1
## 220	1111	0
## 221	1112	1
## 222	1113	0
## 223	1114	1
## 224	1115	0
## 225	1116	1
## 226	1117	1
## 227	1118	0
## 228	1119	1
## 229	1120	0
## 230	1121	0
## 231	1122	0
## 232	1123	1
## 233	1124	0
## 234	1125	0
## 235	1126	0
## 236	1127	0
## 237	1128	0
## 238	1129	0
## 239	1130	1
## 240	1131	1
## 241	1132	1
## 242	1133	1
## 243	1134	0
## 244	1135	0
## 245	1136	0
## 246	1137	0
## 247	1138	1
## 248	1139	0
## 249	1140	1
## 250	1141	1
## 251	1142	1
## 252	1143	0
## 253	1144	0
## 254	1145	0
## 255	1146	0
## 256	1147	0
## 257	1148	0
## 258	1149	0
## 259	1150	1
## 260	1151	0
## 261	1152	0
## 262	1153	0
## 263	1154	1
## 264	1155	1
## 265	1156	0
## 266	1157	0
## 267	1158	0
## 268	1159	0
## 269	1160	0
## 270	1161	0
## 271	1162	0

## 272	1163	0
## 273	1164	1
## 274	1165	1
## 275	1166	0
## 276	1167	1
## 277	1168	0
## 278	1169	0
## 279	1170	0
## 280	1171	0
## 281	1172	0
## 282	1173	1
## 283	1174	1
## 284	1175	1
## 285	1176	0
## 286	1177	0
## 287	1178	0
## 288	1179	0
## 289	1180	0
## 290	1181	0
## 291	1182	0
## 292	1183	1
## 293	1184	0
## 294	1185	0
## 295	1186	0
## 296	1187	0
## 297	1188	1
## 298	1189	0
## 299	1190	0
## 300	1191	0
## 301	1192	0
## 302	1193	0
## 303	1194	0
## 304	1195	0
## 305	1196	1
## 306	1197	1
## 307	1198	0
## 308	1199	1
## 309	1200	0
## 310	1201	1
## 311	1202	0
## 312	1203	0
## 313	1204	0
## 314	1205	1
## 315	1206	1
## 316	1207	1
## 317	1208	0
## 318	1209	0
## 319	1210	0
## 320	1211	0
## 321	1212	0
## 322	1213	0
## 323	1214	0
## 324	1215	0
## 325	1216	1

## 326	1217	0
## 327	1218	1
## 328	1219	0
## 329	1220	0
## 330	1221	0
## 331	1222	1
## 332	1223	0
## 333	1224	0
## 334	1225	1
## 335	1226	0
## 336	1227	0
## 337	1228	0
## 338	1229	0
## 339	1230	0
## 340	1231	0
## 341	1232	0
## 342	1233	0
## 343	1234	0
## 344	1235	1
## 345	1236	0
## 346	1237	0
## 347	1238	0
## 348	1239	1
## 349	1240	0
## 350	1241	1
## 351	1242	1
## 352	1243	0
## 353	1244	0
## 354	1245	0
## 355	1246	0
## 356	1247	0
## 357	1248	1
## 358	1249	0
## 359	1250	0
## 360	1251	1
## 361	1252	0
## 362	1253	1
## 363	1254	1
## 364	1255	0
## 365	1256	1
## 366	1257	0
## 367	1258	0
## 368	1259	0
## 369	1260	1
## 370	1261	0
## 371	1262	0
## 372	1263	1
## 373	1264	0
## 374	1265	0
## 375	1266	1
## 376	1267	1
## 377	1268	0
## 378	1269	0
## 379	1270	0

## 380	1271	0
## 381	1272	0
## 382	1273	0
## 383	1274	1
## 384	1275	1
## 385	1276	0
## 386	1277	1
## 387	1278	0
## 388	1279	0
## 389	1280	0
## 390	1281	0
## 391	1282	0
## 392	1283	1
## 393	1284	0
## 394	1285	0
## 395	1286	0
## 396	1287	1
## 397	1288	0
## 398	1289	1
## 399	1290	0
## 400	1291	0
## 401	1292	1
## 402	1293	0
## 403	1294	1
## 404	1295	0
## 405	1296	0
## 406	1297	0
## 407	1298	0
## 408	1299	0
## 409	1300	1
## 410	1301	1
## 411	1302	1
## 412	1303	1
## 413	1304	0
## 414	1305	0
## 415	1306	1
## 416	1307	0
## 417	1308	0
## 418	1309	0

Improve prediction

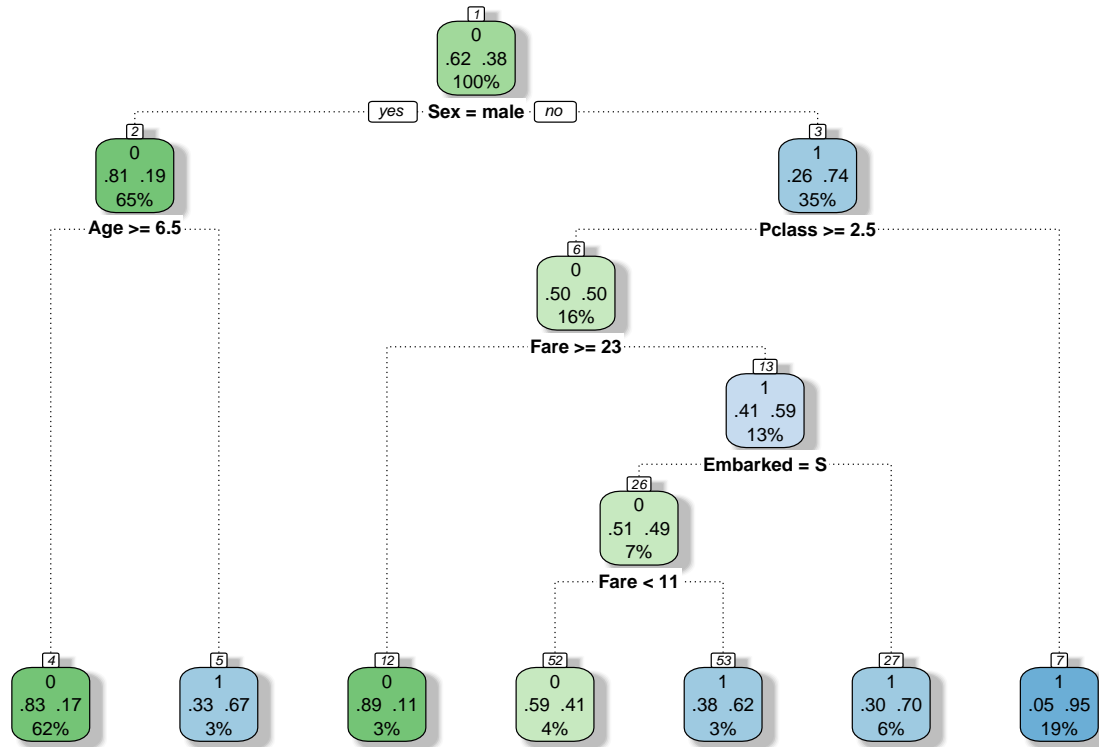
To improve prediction, a valid assumption is that larger families need more time to get together on a sinking ship, and hence have less chance of surviving. Family size is determined by the variables SibSp and Parch, which indicate the number of family members a certain passenger is traveling with. So we need to add a new variable family_size, which is the sum of SibSp and Parch plus one (the observation itself), to the test and train set. In model five another important variable ‘Title’ is added to the decision tree.

```
# Create a new train set with the new variable
train_two <- train
train_two$family_size <- train$SibSp + train$Parch + 1

# Create a new decision tree
```

```
my_tree_four <- rpart(Survived ~ Pclass + Sex + Age + SibSp + Parch + Fare + Embarked + family_size, da

# Visualize new decision tree
fancyRpartPlot(my_tree_four)
```

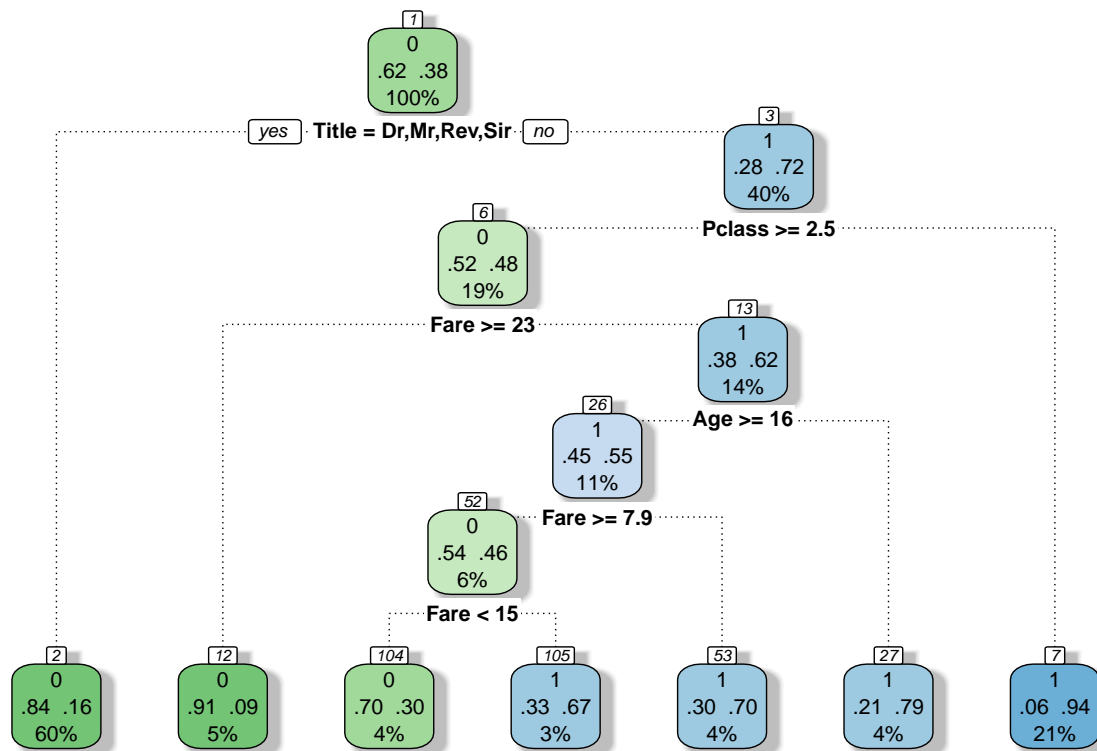


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```
train_new = all_data[1:891,]
train_new = subset(train_new , select = -c(family_size))
test_new = all_data[892:1309,]
test_new = subset(test_new , select = -c(family_size))

# Create a new decision tree
my_tree_five <- rpart(Survived ~ Pclass + Sex + Age + SibSp + Parch + Fare + Embarked + Title,
                      data = train_new, method = 'class')

# Visualize new decision tree
fancyRpartPlot(my_tree_five)
```



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```

# Make prediction using `my_tree_five` and `test_new`
my_prediction <- my_prediction <- predict(my_tree_five, test_new, type = 'class')

# Create a data frame with two columns: PassengerId & Survived. Survived contains predictions
my_solution2 <- data.frame(PassengerId = test_new$PassengerId, Survived = my_prediction)

# Write solution away to a csv file with the name my_solution.csv
write.csv(my_solution2, file = 'my_solution2.csv', row.names = FALSE)

# View my_solution2
my_solution2

```

```

##      PassengerId Survived
## 892           892         0
## 893           893         1
## 894           894         0
## 895           895         0
## 896           896         0
## 897           897         0
## 898           898         1
## 899           899         0
## 900           900         1
## 901           901         0
## 902           902         0
## 903           903         0
## 904           904         1
## 905           905         0

```

## 906	906	1
## 907	907	1
## 908	908	0
## 909	909	0
## 910	910	0
## 911	911	1
## 912	912	0
## 913	913	1
## 914	914	1
## 915	915	0
## 916	916	1
## 917	917	0
## 918	918	1
## 919	919	0
## 920	920	0
## 921	921	0
## 922	922	0
## 923	923	0
## 924	924	1
## 925	925	0
## 926	926	0
## 927	927	0
## 928	928	0
## 929	929	0
## 930	930	0
## 931	931	0
## 932	932	0
## 933	933	0
## 934	934	0
## 935	935	1
## 936	936	1
## 937	937	0
## 938	938	0
## 939	939	0
## 940	940	1
## 941	941	1
## 942	942	0
## 943	943	0
## 944	944	1
## 945	945	1
## 946	946	0
## 947	947	0
## 948	948	0
## 949	949	0
## 950	950	0
## 951	951	1
## 952	952	0
## 953	953	0
## 954	954	0
## 955	955	1
## 956	956	1
## 957	957	1
## 958	958	1
## 959	959	0

## 960	960	0
## 961	961	1
## 962	962	1
## 963	963	0
## 964	964	0
## 965	965	0
## 966	966	1
## 967	967	0
## 968	968	0
## 969	969	1
## 970	970	0
## 971	971	1
## 972	972	1
## 973	973	0
## 974	974	0
## 975	975	0
## 976	976	0
## 977	977	0
## 978	978	1
## 979	979	0
## 980	980	1
## 981	981	1
## 982	982	0
## 983	983	0
## 984	984	1
## 985	985	0
## 986	986	0
## 987	987	0
## 988	988	1
## 989	989	0
## 990	990	1
## 991	991	0
## 992	992	1
## 993	993	0
## 994	994	0
## 995	995	0
## 996	996	1
## 997	997	0
## 998	998	0
## 999	999	0
## 1000	1000	0
## 1001	1001	0
## 1002	1002	0
## 1003	1003	1
## 1004	1004	1
## 1005	1005	1
## 1006	1006	1
## 1007	1007	0
## 1008	1008	0
## 1009	1009	1
## 1010	1010	0
## 1011	1011	1
## 1012	1012	1
## 1013	1013	0

## 1014	1014	1
## 1015	1015	0
## 1016	1016	0
## 1017	1017	1
## 1018	1018	0
## 1019	1019	1
## 1020	1020	0
## 1021	1021	0
## 1022	1022	0
## 1023	1023	1
## 1024	1024	0
## 1025	1025	0
## 1026	1026	0
## 1027	1027	0
## 1028	1028	0
## 1029	1029	0
## 1030	1030	0
## 1031	1031	0
## 1032	1032	0
## 1033	1033	1
## 1034	1034	0
## 1035	1035	0
## 1036	1036	0
## 1037	1037	0
## 1038	1038	0
## 1039	1039	0
## 1040	1040	0
## 1041	1041	0
## 1042	1042	1
## 1043	1043	0
## 1044	1044	0
## 1045	1045	0
## 1046	1046	0
## 1047	1047	0
## 1048	1048	1
## 1049	1049	1
## 1050	1050	0
## 1051	1051	0
## 1052	1052	1
## 1053	1053	1
## 1054	1054	1
## 1055	1055	0
## 1056	1056	0
## 1057	1057	1
## 1058	1058	0
## 1059	1059	0
## 1060	1060	1
## 1061	1061	0
## 1062	1062	0
## 1063	1063	0
## 1064	1064	0
## 1065	1065	0
## 1066	1066	0
## 1067	1067	1

## 1068	1068	1
## 1069	1069	0
## 1070	1070	1
## 1071	1071	1
## 1072	1072	0
## 1073	1073	0
## 1074	1074	1
## 1075	1075	0
## 1076	1076	1
## 1077	1077	0
## 1078	1078	1
## 1079	1079	0
## 1080	1080	0
## 1081	1081	0
## 1082	1082	0
## 1083	1083	0
## 1084	1084	1
## 1085	1085	0
## 1086	1086	1
## 1087	1087	0
## 1088	1088	1
## 1089	1089	1
## 1090	1090	0
## 1091	1091	0
## 1092	1092	1
## 1093	1093	1
## 1094	1094	1
## 1095	1095	1
## 1096	1096	0
## 1097	1097	0
## 1098	1098	1
## 1099	1099	0
## 1100	1100	1
## 1101	1101	0
## 1102	1102	0
## 1103	1103	0
## 1104	1104	0
## 1105	1105	1
## 1106	1106	1
## 1107	1107	0
## 1108	1108	1
## 1109	1109	0
## 1110	1110	1
## 1111	1111	0
## 1112	1112	1
## 1113	1113	0
## 1114	1114	1
## 1115	1115	0
## 1116	1116	1
## 1117	1117	1
## 1118	1118	0
## 1119	1119	1
## 1120	1120	0
## 1121	1121	0

## 1122	1122	0
## 1123	1123	1
## 1124	1124	0
## 1125	1125	0
## 1126	1126	0
## 1127	1127	0
## 1128	1128	0
## 1129	1129	0
## 1130	1130	1
## 1131	1131	1
## 1132	1132	1
## 1133	1133	1
## 1134	1134	0
## 1135	1135	0
## 1136	1136	0
## 1137	1137	0
## 1138	1138	1
## 1139	1139	0
## 1140	1140	1
## 1141	1141	0
## 1142	1142	1
## 1143	1143	0
## 1144	1144	0
## 1145	1145	0
## 1146	1146	0
## 1147	1147	0
## 1148	1148	0
## 1149	1149	0
## 1150	1150	1
## 1151	1151	0
## 1152	1152	0
## 1153	1153	0
## 1154	1154	1
## 1155	1155	1
## 1156	1156	0
## 1157	1157	0
## 1158	1158	0
## 1159	1159	0
## 1160	1160	0
## 1161	1161	0
## 1162	1162	0
## 1163	1163	0
## 1164	1164	1
## 1165	1165	1
## 1166	1166	0
## 1167	1167	1
## 1168	1168	0
## 1169	1169	0
## 1170	1170	0
## 1171	1171	0
## 1172	1172	0
## 1173	1173	1
## 1174	1174	1
## 1175	1175	1

## 1176	1176	1
## 1177	1177	0
## 1178	1178	0
## 1179	1179	0
## 1180	1180	0
## 1181	1181	0
## 1182	1182	0
## 1183	1183	1
## 1184	1184	0
## 1185	1185	0
## 1186	1186	0
## 1187	1187	0
## 1188	1188	1
## 1189	1189	0
## 1190	1190	0
## 1191	1191	0
## 1192	1192	0
## 1193	1193	0
## 1194	1194	0
## 1195	1195	0
## 1196	1196	1
## 1197	1197	1
## 1198	1198	0
## 1199	1199	1
## 1200	1200	0
## 1201	1201	0
## 1202	1202	0
## 1203	1203	0
## 1204	1204	0
## 1205	1205	1
## 1206	1206	1
## 1207	1207	1
## 1208	1208	0
## 1209	1209	0
## 1210	1210	0
## 1211	1211	0
## 1212	1212	0
## 1213	1213	0
## 1214	1214	0
## 1215	1215	0
## 1216	1216	1
## 1217	1217	0
## 1218	1218	1
## 1219	1219	0
## 1220	1220	0
## 1221	1221	0
## 1222	1222	1
## 1223	1223	0
## 1224	1224	0
## 1225	1225	1
## 1226	1226	0
## 1227	1227	0
## 1228	1228	0
## 1229	1229	0

## 1230	1230	0
## 1231	1231	1
## 1232	1232	0
## 1233	1233	0
## 1234	1234	0
## 1235	1235	1
## 1236	1236	1
## 1237	1237	1
## 1238	1238	0
## 1239	1239	1
## 1240	1240	0
## 1241	1241	1
## 1242	1242	1
## 1243	1243	0
## 1244	1244	0
## 1245	1245	0
## 1246	1246	1
## 1247	1247	0
## 1248	1248	1
## 1249	1249	0
## 1250	1250	0
## 1251	1251	1
## 1252	1252	0
## 1253	1253	1
## 1254	1254	1
## 1255	1255	0
## 1256	1256	1
## 1257	1257	0
## 1258	1258	0
## 1259	1259	0
## 1260	1260	1
## 1261	1261	0
## 1262	1262	0
## 1263	1263	1
## 1264	1264	0
## 1265	1265	0
## 1266	1266	1
## 1267	1267	1
## 1268	1268	0
## 1269	1269	0
## 1270	1270	0
## 1271	1271	0
## 1272	1272	0
## 1273	1273	0
## 1274	1274	0
## 1275	1275	1
## 1276	1276	0
## 1277	1277	1
## 1278	1278	0
## 1279	1279	0
## 1280	1280	0
## 1281	1281	1
## 1282	1282	0
## 1283	1283	1

```
## 1284      1284      1
## 1285      1285      0
## 1286      1286      0
## 1287      1287      1
## 1288      1288      0
## 1289      1289      1
## 1290      1290      0
## 1291      1291      0
## 1292      1292      1
## 1293      1293      0
## 1294      1294      1
## 1295      1295      0
## 1296      1296      0
## 1297      1297      0
## 1298      1298      0
## 1299      1299      0
## 1300      1300      1
## 1301      1301      1
## 1302      1302      1
## 1303      1303      1
## 1304      1304      1
## 1305      1305      0
## 1306      1306      1
## 1307      1307      0
## 1308      1308      0
## 1309      1309      1
```

Random Forest

Random forest technique handles the overfitting problem faced in decision trees. To implement Random Forest all the missing values in the data set should be filled via prediction model.

```
# All data, both training and test set
str(all_data)
```

```
## 'data.frame':  1309 obs. of  14 variables:
## $ PassengerId: int  1 2 3 4 5 6 7 8 9 10 ...
## $ Survived   : int  0 1 1 1 0 0 0 0 1 1 ...
## $ Pclass     : int  3 1 3 1 3 3 1 3 3 2 ...
## $ Name       : chr  "Braund, Mr. Owen Harris" "Cumings, Mrs. John Bradley (Florence Briggs Thayer)"
## $ Sex        : Factor w/ 2 levels "female","male": 2 1 1 1 2 2 2 2 1 1 ...
## $ Age        : num  22 38 26 35 35 NA 54 2 27 14 ...
## $ SibSp      : int  1 1 0 1 0 0 0 3 0 1 ...
## $ Parch      : int  0 0 0 0 0 0 0 1 2 0 ...
## $ Ticket     : Factor w/ 929 levels "110152","110413",...: 524 597 670 50 473 276 86 396 345 133 ...
## $ Fare       : num  7.25 71.28 7.92 53.1 8.05 ...
## $ Cabin      : Factor w/ 187 levels "", "A10", "A14",...: 1 83 1 57 1 1 131 1 1 1 ...
## $ Embarked   : Factor w/ 4 levels "", "C", "Q", "S": 4 2 4 4 4 3 4 4 4 2 ...
## $ family_size: num  2 2 1 2 1 1 1 5 3 2 ...
## $ Title      : Factor w/ 11 levels "Col","Dr","Lady",...: 7 8 5 8 7 7 7 4 8 8 ...
```

```

# Passenger on row 62 and 830 do not have a value for embarkment.
# Since many passengers embarked at Southampton, we give them the value S.
# Code all embarkment codes as factors.
all_data$Embarked[c(62,830)] = "S"
all_data$Embarked <- factor(all_data$Embarked)

# Passenger on row 1044 has an NA Fare value. Replace it with the median fare value.
all_data$Fare[1044] <- median(all_data$Fare, na.rm=TRUE)

# To fill the missing age value
# Make a prediction of a passengers Age using the other variables and a decision tree model.
# method="anova" is used since we are predicting a continuous variable.
predicted_age <- rpart(Age ~ Pclass + Sex + SibSp + Parch + Fare + Embarked + Title + family_size,
                      data=all_data[!is.na(all_data$Age),], method="anova")
all_data$Age[is.na(all_data$Age)] <- predict(predicted_age, all_data[is.na(all_data$Age),])

# Split the data back into a train set and a test set
train <- all_data[1:891,]
test <- all_data[892:1309,]

# Set seed for reproducibility
set.seed(111)

# Apply the Random Forest Algorithm
my_forest <- randomForest(as.factor(Survived) ~ Pclass + Sex + Age + SibSp + Parch + Fare + Embarked + Title,
                          data=train, importance=TRUE, ntree=1000)

# Make prediction using the test set
my_prediction <- predict(my_forest, test)

# Create a data frame with two columns: PassengerId & Survived. Survived contains predictions
my_solution3 <- data.frame(PassengerId = test$PassengerId, Survived = my_prediction)

# Write solution away to a csv file with the name my_solution.csv
write.csv(my_solution3, file = "my_solution3.csv", row.names = FALSE)

# View my_solution3
my_solution3

```

```

##      PassengerId Survived
## 892           892        0
## 893           893        0
## 894           894        0
## 895           895        0
## 896           896        1
## 897           897        0
## 898           898        0
## 899           899        0
## 900           900        1
## 901           901        0
## 902           902        0
## 903           903        0
## 904           904        1

```


## 905	905	0
## 906	906	1
## 907	907	1
## 908	908	0
## 909	909	0
## 910	910	0
## 911	911	1
## 912	912	0
## 913	913	1
## 914	914	1
## 915	915	0
## 916	916	1
## 917	917	0
## 918	918	1
## 919	919	0
## 920	920	0
## 921	921	0
## 922	922	0
## 923	923	0
## 924	924	1
## 925	925	0
## 926	926	1
## 927	927	0
## 928	928	0
## 929	929	0
## 930	930	0
## 931	931	1
## 932	932	0
## 933	933	0
## 934	934	0
## 935	935	1
## 936	936	1
## 937	937	0
## 938	938	0
## 939	939	0
## 940	940	1
## 941	941	1
## 942	942	0
## 943	943	0
## 944	944	1
## 945	945	1
## 946	946	0
## 947	947	0
## 948	948	0
## 949	949	0
## 950	950	0
## 951	951	1
## 952	952	0
## 953	953	0
## 954	954	0
## 955	955	1
## 956	956	1
## 957	957	1
## 958	958	1

## 959	959	0
## 960	960	0
## 961	961	1
## 962	962	1
## 963	963	0
## 964	964	0
## 965	965	0
## 966	966	1
## 967	967	0
## 968	968	0
## 969	969	1
## 970	970	0
## 971	971	1
## 972	972	1
## 973	973	0
## 974	974	0
## 975	975	0
## 976	976	0
## 977	977	0
## 978	978	1
## 979	979	0
## 980	980	1
## 981	981	1
## 982	982	1
## 983	983	0
## 984	984	1
## 985	985	0
## 986	986	0
## 987	987	0
## 988	988	1
## 989	989	0
## 990	990	0
## 991	991	0
## 992	992	1
## 993	993	0
## 994	994	0
## 995	995	0
## 996	996	1
## 997	997	0
## 998	998	0
## 999	999	0
## 1000	1000	0
## 1001	1001	0
## 1002	1002	0
## 1003	1003	1
## 1004	1004	1
## 1005	1005	1
## 1006	1006	1
## 1007	1007	0
## 1008	1008	0
## 1009	1009	1
## 1010	1010	0
## 1011	1011	1
## 1012	1012	1

## 1013	1013	0
## 1014	1014	1
## 1015	1015	0
## 1016	1016	0
## 1017	1017	1
## 1018	1018	0
## 1019	1019	1
## 1020	1020	0
## 1021	1021	0
## 1022	1022	0
## 1023	1023	0
## 1024	1024	0
## 1025	1025	0
## 1026	1026	0
## 1027	1027	0
## 1028	1028	0
## 1029	1029	0
## 1030	1030	0
## 1031	1031	0
## 1032	1032	0
## 1033	1033	1
## 1034	1034	0
## 1035	1035	0
## 1036	1036	0
## 1037	1037	0
## 1038	1038	0
## 1039	1039	0
## 1040	1040	0
## 1041	1041	0
## 1042	1042	1
## 1043	1043	0
## 1044	1044	0
## 1045	1045	1
## 1046	1046	0
## 1047	1047	0
## 1048	1048	1
## 1049	1049	0
## 1050	1050	0
## 1051	1051	1
## 1052	1052	1
## 1053	1053	1
## 1054	1054	1
## 1055	1055	0
## 1056	1056	0
## 1057	1057	1
## 1058	1058	0
## 1059	1059	0
## 1060	1060	1
## 1061	1061	0
## 1062	1062	0
## 1063	1063	0
## 1064	1064	0
## 1065	1065	0
## 1066	1066	0

## 1067	1067	1
## 1068	1068	1
## 1069	1069	0
## 1070	1070	1
## 1071	1071	1
## 1072	1072	0
## 1073	1073	0
## 1074	1074	1
## 1075	1075	0
## 1076	1076	1
## 1077	1077	0
## 1078	1078	1
## 1079	1079	0
## 1080	1080	0
## 1081	1081	0
## 1082	1082	0
## 1083	1083	0
## 1084	1084	1
## 1085	1085	0
## 1086	1086	1
## 1087	1087	0
## 1088	1088	1
## 1089	1089	1
## 1090	1090	0
## 1091	1091	0
## 1092	1092	1
## 1093	1093	1
## 1094	1094	1
## 1095	1095	1
## 1096	1096	0
## 1097	1097	0
## 1098	1098	1
## 1099	1099	0
## 1100	1100	1
## 1101	1101	0
## 1102	1102	0
## 1103	1103	0
## 1104	1104	0
## 1105	1105	1
## 1106	1106	0
## 1107	1107	0
## 1108	1108	1
## 1109	1109	0
## 1110	1110	1
## 1111	1111	0
## 1112	1112	1
## 1113	1113	0
## 1114	1114	1
## 1115	1115	0
## 1116	1116	1
## 1117	1117	1
## 1118	1118	0
## 1119	1119	1
## 1120	1120	0

## 1121	1121	0
## 1122	1122	0
## 1123	1123	1
## 1124	1124	0
## 1125	1125	0
## 1126	1126	0
## 1127	1127	0
## 1128	1128	0
## 1129	1129	0
## 1130	1130	1
## 1131	1131	1
## 1132	1132	1
## 1133	1133	1
## 1134	1134	0
## 1135	1135	0
## 1136	1136	1
## 1137	1137	0
## 1138	1138	1
## 1139	1139	0
## 1140	1140	1
## 1141	1141	0
## 1142	1142	1
## 1143	1143	0
## 1144	1144	0
## 1145	1145	0
## 1146	1146	0
## 1147	1147	0
## 1148	1148	0
## 1149	1149	0
## 1150	1150	1
## 1151	1151	0
## 1152	1152	0
## 1153	1153	0
## 1154	1154	1
## 1155	1155	1
## 1156	1156	0
## 1157	1157	0
## 1158	1158	0
## 1159	1159	0
## 1160	1160	0
## 1161	1161	0
## 1162	1162	0
## 1163	1163	0
## 1164	1164	1
## 1165	1165	1
## 1166	1166	0
## 1167	1167	1
## 1168	1168	0
## 1169	1169	0
## 1170	1170	0
## 1171	1171	0
## 1172	1172	0
## 1173	1173	1
## 1174	1174	1

## 1175	1175	0
## 1176	1176	1
## 1177	1177	0
## 1178	1178	0
## 1179	1179	0
## 1180	1180	0
## 1181	1181	0
## 1182	1182	0
## 1183	1183	0
## 1184	1184	0
## 1185	1185	0
## 1186	1186	0
## 1187	1187	0
## 1188	1188	1
## 1189	1189	0
## 1190	1190	0
## 1191	1191	0
## 1192	1192	0
## 1193	1193	0
## 1194	1194	0
## 1195	1195	0
## 1196	1196	1
## 1197	1197	1
## 1198	1198	0
## 1199	1199	1
## 1200	1200	0
## 1201	1201	0
## 1202	1202	0
## 1203	1203	0
## 1204	1204	0
## 1205	1205	0
## 1206	1206	1
## 1207	1207	1
## 1208	1208	0
## 1209	1209	0
## 1210	1210	0
## 1211	1211	0
## 1212	1212	0
## 1213	1213	0
## 1214	1214	0
## 1215	1215	1
## 1216	1216	1
## 1217	1217	0
## 1218	1218	1
## 1219	1219	0
## 1220	1220	0
## 1221	1221	0
## 1222	1222	1
## 1223	1223	0
## 1224	1224	0
## 1225	1225	1
## 1226	1226	0
## 1227	1227	0
## 1228	1228	0

## 1229	1229	0
## 1230	1230	0
## 1231	1231	1
## 1232	1232	0
## 1233	1233	0
## 1234	1234	0
## 1235	1235	1
## 1236	1236	1
## 1237	1237	1
## 1238	1238	0
## 1239	1239	1
## 1240	1240	0
## 1241	1241	1
## 1242	1242	1
## 1243	1243	0
## 1244	1244	0
## 1245	1245	0
## 1246	1246	1
## 1247	1247	0
## 1248	1248	1
## 1249	1249	0
## 1250	1250	0
## 1251	1251	1
## 1252	1252	0
## 1253	1253	1
## 1254	1254	1
## 1255	1255	0
## 1256	1256	1
## 1257	1257	0
## 1258	1258	0
## 1259	1259	0
## 1260	1260	1
## 1261	1261	0
## 1262	1262	0
## 1263	1263	1
## 1264	1264	0
## 1265	1265	0
## 1266	1266	1
## 1267	1267	1
## 1268	1268	0
## 1269	1269	0
## 1270	1270	0
## 1271	1271	0
## 1272	1272	0
## 1273	1273	0
## 1274	1274	1
## 1275	1275	1
## 1276	1276	0
## 1277	1277	1
## 1278	1278	0
## 1279	1279	0
## 1280	1280	0
## 1281	1281	0
## 1282	1282	0

## 1283	1283	1
## 1284	1284	1
## 1285	1285	0
## 1286	1286	0
## 1287	1287	1
## 1288	1288	0
## 1289	1289	1
## 1290	1290	0
## 1291	1291	0
## 1292	1292	1
## 1293	1293	0
## 1294	1294	1
## 1295	1295	0
## 1296	1296	0
## 1297	1297	0
## 1298	1298	0
## 1299	1299	0
## 1300	1300	1
## 1301	1301	1
## 1302	1302	1
## 1303	1303	1
## 1304	1304	0
## 1305	1305	0
## 1306	1306	1
## 1307	1307	0
## 1308	1308	0
## 1309	1309	1