

Milestone 4

Group D

2024-10-21

R Markdown

Loading all the required packages

```
# Load the randomForest package
# This package is used to build random forest models.
library(randomForest)

## randomForest 4.7-1.2
## Type rfNews() to see new features/changes/bug fixes.

# Load the caret package
# It provides functions for data preprocessing, model training, tuning, evaluation,
# and visualization of performance metrics.
library(caret)

## Loading required package: ggplot2
##
## Attaching package: 'ggplot2'
## The following object is masked from 'package:randomForest':
##
##     margin
## Loading required package: lattice

# Load the party package
# The party package provides tools for creating recursive partitioning models like decision trees.
library(party)

## Loading required package: grid
## Loading required package: mvtnorm
## Loading required package: modeltools
## Loading required package: stats4
## Loading required package: strucchange
## Loading required package: zoo
##
## Attaching package: 'zoo'
## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric
```

```
## Loading required package: sandwich
# Load the partykit package
# partykit is an extension of the party package, focused on improving the visualization and
# handling of decision trees and model objects.
library(partykit)

## Loading required package: libcoin

##
## Attaching package: 'partykit'

## The following objects are masked from 'package:party':
##
##      cforest, ctree, ctree_control, edge_simple, mob, mob_control,
##      node_barplot, node_bivplot, node_boxplot, node_inner, node_surv,
##      node_terminal, varimp
# Load the rpart package
# rpart (Recursive Partitioning and Regression Trees) is used to create decision trees
# for classification or regression problems.
library(rpart)

# Load the rpart.plot package
# This package is used to visualize decision trees created using the rpart package.
# It creates detailed and customizable plots of decision trees, making it easier to interpret
# the splits and decision rules.
library(rpart.plot)

#Load library for partial dependence plots
library(pdp)

data <- read.csv("Prepared_Data (1).csv")
```

Creating the “eligibility” column

```
data$eligibility <- ifelse(data$Annual.Salary > 50000 &
                          data$yrs_residence > 3 & data$Gross_Year_To_Date > 45000, 1, 0)
data$eligibility <- as.factor(data$eligibility)
```

Splitting of the data sets into training and testing, 75% and 25%, respectively

```
set.seed(123)
trainIndex <- createDataPartition(data$eligibility, p = 0.75, list = FALSE)
trainData <- data[trainIndex, ]
testData <- data[-trainIndex, ]
```

Selecting the relevant features

```
features <- c("Gross_Pay_Last_Paycheck", "Gross_Year_To_Date",
              "Gross_FRS_Contribution", "household_size",
              "yrs_residence", "Annual.Salary", "marital_status", "Age")
```

Building the random forest model

```
rf_model <- randomForest(as.factor(eligibility) ~ .,  
                        data = trainData[, c(features, "eligibility")],  
                        importance = TRUE, ntree = 10)
```

Predictions on the test set

```
predictions <- predict(rf_model, newdata = testData[, features])
```

Produce the confusion matrix

```
conf_matrix <- confusionMatrix(predictions, testData$eligibility)  
print(conf_matrix)
```

```
## Confusion Matrix and Statistics  
##  
##           Reference  
## Prediction      0      1  
##           0 34945      4  
##           1      0 11314  
##  
##           Accuracy : 0.9999  
##           95% CI : (0.9998, 1)  
##      No Information Rate : 0.7554  
##      P-Value [Acc > NIR] : <2e-16  
##  
##           Kappa : 0.9998  
##  
##      McNemar's Test P-Value : 0.1336  
##  
##           Sensitivity : 1.0000  
##           Specificity : 0.9996  
##      Pos Pred Value : 0.9999  
##      Neg Pred Value : 1.0000  
##           Prevalence : 0.7554  
##      Detection Rate : 0.7554  
##      Detection Prevalence : 0.7554  
##      Balanced Accuracy : 0.9998  
##  
##      'Positive' Class : 0  
##
```

Classification report (including precision, recall, and F1-score)

```
precision <- posPredValue(predictions, testData$eligibility)  
recall <- sensitivity(predictions, testData$eligibility)  
f1_score <- (2 * precision * recall) / (precision + recall)  
cat("Precision:", precision, "\nRecall:", recall, "\nF1-score:", f1_score, "\n")
```

```
## Precision: 0.9998855
```

```
## Recall: 1
## F1-score: 0.9999428
```

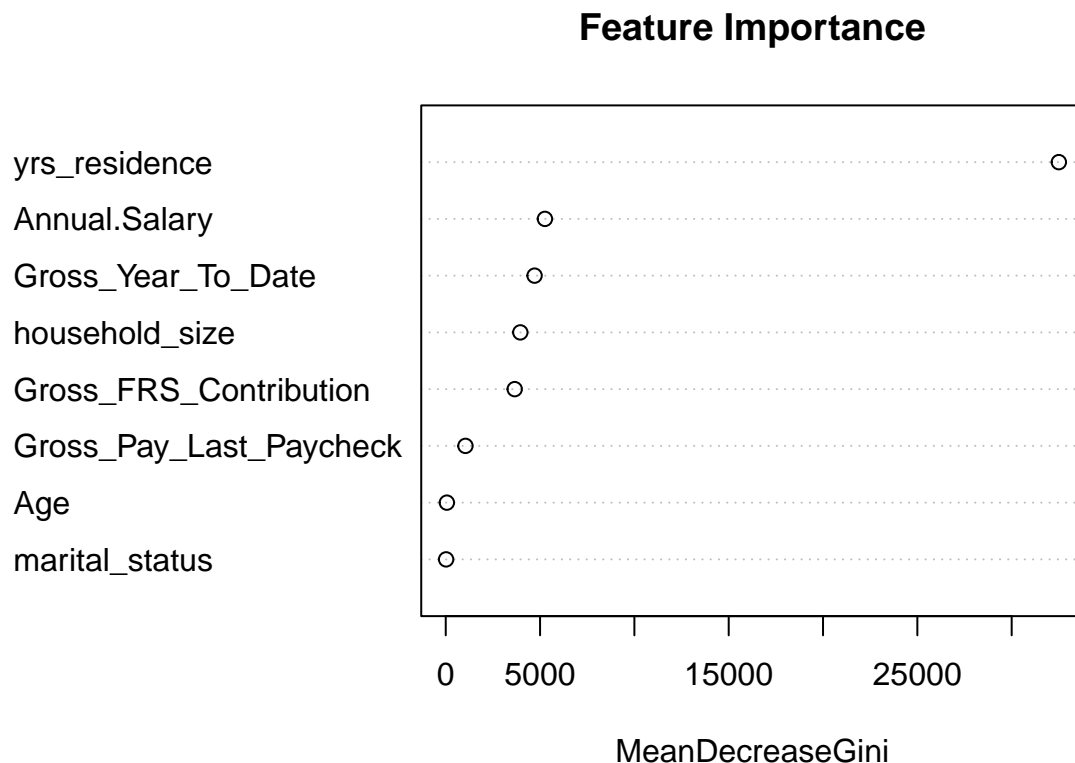
Calculate and rank feature importance

```
importance_values <- importance(rf_model)
feature_importance <- data.frame(Feature = rownames(importance_values),
                                Importance = importance_values[, "MeanDecreaseGini"])
feature_importance <- feature_importance[order(-feature_importance$Importance), ]
print(feature_importance)
```

```
##               Feature Importance
## yrs_residence      yrs_residence 32501.37101
## Annual.Salary      Annual.Salary  5257.40599
## Gross_Year_To_Date Gross_Year_To_Date 4709.18636
## household_size      household_size 3953.27263
## Gross_FRS_Contribution Gross_FRS_Contribution 3654.69945
## Gross_Pay_Last_Paycheck Gross_Pay_Last_Paycheck 1043.87228
## Age                Age          58.77853
## marital_status      marital_status  19.12357
```

Plotting feature importance

```
varImpPlot(rf_model,
            main = "Feature Importance",
            n.var = min(10, nrow(importance(rf_model))), # Show top 10 important features
            type = 2) # 'type = 2' is for Mean Decrease in Gini
```



Features with higher bars are more important for the model's decision-making process. They contribute more to reducing uncertainty or impurity when splitting the data.

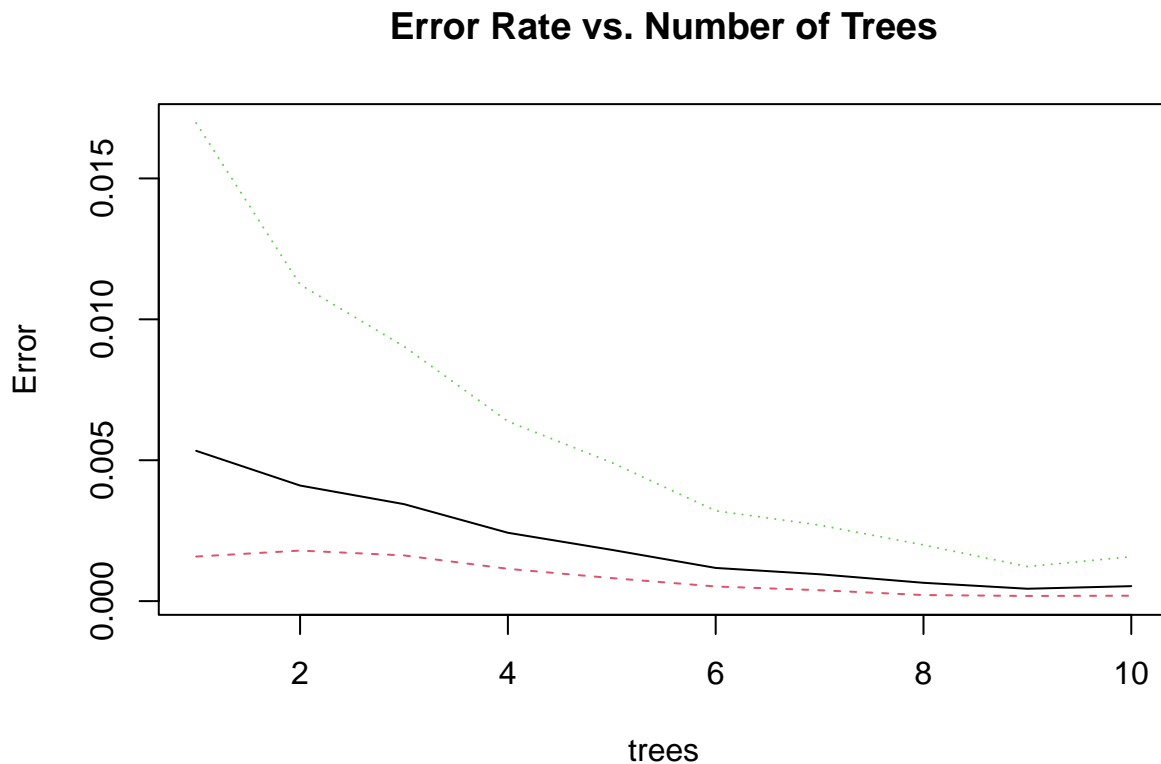
If a feature like Annual.Salary has a much higher importance score than others, it indicates that the Random Forest relies heavily on this feature to classify customers as eligible or not.

Relative importance is key: even if two features have importance values of 10,000 and 5,000 respectively, the one with 10,000 is twice as influential for the model.

This helps identify which features could be prioritized for further analysis or used in simpler models for a similar performance.

Plotting the error rate of the random forest model

```
plot(rf_model, main = "Error Rate vs. Number of Trees")
```



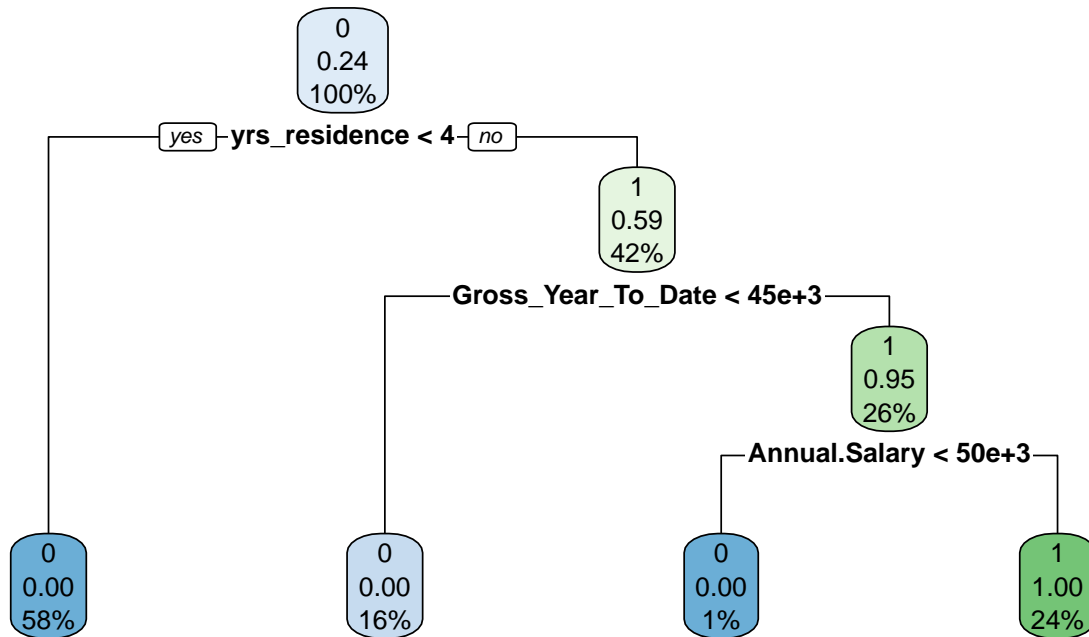
Decreasing Error Rate: If the error rate decreases as more trees are added, it means that the Random Forest is improving its performance. However, this trend usually plateaus after a certain point.

Point of Convergence: The number of trees after which the error rate plateaus is an indicator that adding more trees won't significantly improve performance. For instance, if the error rate levels off around 200 trees, using 500 trees may not provide substantial benefit.

Fit a decision tree using rpart on the same data

```
tree_model <- rpart(as.factor(eligibility) ~ ., data = trainData[, c(features, "eligibility")])  
  
# Plot the decision tree  
rpart.plot(tree_model, main = "Decision Tree Approximation")
```

Decision Tree Approximation



Extract and print the structure of the first tree from the random forest
`print(getTree(rf_model, k = 1, labelVar = TRUE))`

##	left daughter	right daughter	split var	split point	status
## 1	2	3	Gross_FRS_Contribution	43843.880	1
## 2	4	5	Gross_Pay_Last_Paycheck	2126.000	1
## 3	6	7	marital_status	1.500	1
## 4	8	9	marital_status	2.500	1
## 5	10	11	Gross_Year_To_Date	45025.300	1
## 6	12	13	Annual.Salary	51599.470	1
## 7	14	15	household_size	2.500	1
## 8	0	0	<NA>	0.000	-1
## 9	16	17	Gross_Pay_Last_Paycheck	1985.665	1
## 10	0	0	<NA>	0.000	-1
## 11	18	19	household_size	2.500	1
## 12	20	21	Annual.Salary	50046.880	1
## 13	22	23	yrs_residence	3.500	1
## 14	24	25	Gross_Pay_Last_Paycheck	2035.470	1
## 15	26	27	Annual.Salary	49996.050	1
## 16	28	29	yrs_residence	3.500	1
## 17	30	31	Gross_FRS_Contribution	43716.615	1
## 18	32	33	Annual.Salary	61120.540	1
## 19	34	35	Age	75.000	1
## 20	0	0	<NA>	0.000	-1
## 21	36	37	Gross_Pay_Last_Paycheck	2634.980	1
## 22	0	0	<NA>	0.000	-1
## 23	0	0	<NA>	0.000	-1
## 24	38	39	yrs_residence	3.500	1
## 25	40	41	Gross_Pay_Last_Paycheck	2797.405	1
## 26	0	0	<NA>	0.000	-1

## 27	42	43	Gross_FRS_Contribution	44209.575	1
## 28	0	0	<NA>	0.000	-1
## 29	44	45	Annual.Salary	89438.570	1
## 30	0	0	<NA>	0.000	-1
## 31	46	47	Annual.Salary	50958.960	1
## 32	48	49	yrs_residence	3.500	1
## 33	50	51	Annual.Salary	62880.870	1
## 34	52	53	Gross_Pay_Last_Paycheck	2793.295	1
## 35	0	0	<NA>	0.000	-1
## 36	54	55	yrs_residence	3.500	1
## 37	0	0	<NA>	0.000	-1
## 38	0	0	<NA>	0.000	-1
## 39	56	57	Gross_Pay_Last_Paycheck	1575.940	1
## 40	58	59	Annual.Salary	50030.370	1
## 41	60	61	Annual.Salary	49996.570	1
## 42	62	63	Gross_Pay_Last_Paycheck	2035.470	1
## 43	64	65	Age	50.500	1
## 44	0	0	<NA>	0.000	-1
## 45	66	67	yrs_residence	4.500	1
## 46	68	69	Gross_Year_To_Date	45054.320	1
## 47	0	0	<NA>	0.000	-1
## 48	0	0	<NA>	0.000	-1
## 49	70	71	Gross_FRS_Contribution	43750.025	1
## 50	0	0	<NA>	0.000	-1
## 51	0	0	<NA>	0.000	-1
## 52	72	73	Gross_FRS_Contribution	43818.050	1
## 53	0	0	<NA>	0.000	-1
## 54	0	0	<NA>	0.000	-1
## 55	0	0	<NA>	0.000	-1
## 56	74	75	Annual.Salary	51062.440	1
## 57	0	0	<NA>	0.000	-1
## 58	0	0	<NA>	0.000	-1
## 59	76	77	Annual.Salary	51867.140	1
## 60	0	0	<NA>	0.000	-1
## 61	78	79	Gross_Pay_Last_Paycheck	9698.370	1
## 62	0	0	<NA>	0.000	-1
## 63	80	81	Gross_Year_To_Date	44655.830	1
## 64	82	83	Annual.Salary	54545.660	1
## 65	0	0	<NA>	0.000	-1
## 66	84	85	Gross_Pay_Last_Paycheck	1204.015	1
## 67	0	0	<NA>	0.000	-1
## 68	86	87	marital_status	3.500	1
## 69	0	0	<NA>	0.000	-1
## 70	88	89	Gross_Year_To_Date	45031.460	1
## 71	90	91	Gross_Pay_Last_Paycheck	2198.060	1
## 72	0	0	<NA>	0.000	-1
## 73	0	0	<NA>	0.000	-1
## 74	0	0	<NA>	0.000	-1
## 75	0	0	<NA>	0.000	-1
## 76	92	93	marital_status	3.500	1
## 77	94	95	yrs_residence	3.500	1
## 78	96	97	Gross_FRS_Contribution	120996.670	1
## 79	98	99	Age	82.500	1
## 80	0	0	<NA>	0.000	-1

## 81	0	0	<NA>	0.000	-1
## 82	100	101	Gross_Year_To_Date	45261.295	1
## 83	0	0	<NA>	0.000	-1
## 84	0	0	<NA>	0.000	-1
## 85	0	0	<NA>	0.000	-1
## 86	0	0	<NA>	0.000	-1
## 87	0	0	<NA>	0.000	-1
## 88	102	103	Age	58.000	1
## 89	0	0	<NA>	0.000	-1
## 90	104	105	marital_status	3.500	1
## 91	106	107	Age	62.000	1
## 92	108	109	Gross_FRS_Contribution	84059.910	1
## 93	110	111	Annual.Salary	51376.260	1
## 94	0	0	<NA>	0.000	-1
## 95	112	113	Gross_Year_To_Date	44984.935	1
## 96	114	115	Gross_FRS_Contribution	114264.715	1
## 97	116	117	Gross_Pay_Last_Paycheck	5030.860	1
## 98	118	119	yrs_residence	3.500	1
## 99	120	121	marital_status	2.500	1
## 100	0	0	<NA>	0.000	-1
## 101	0	0	<NA>	0.000	-1
## 102	0	0	<NA>	0.000	-1
## 103	122	123	Gross_Year_To_Date	45027.230	1
## 104	124	125	Gross_FRS_Contribution	43753.865	1
## 105	0	0	<NA>	0.000	-1
## 106	0	0	<NA>	0.000	-1
## 107	126	127	Gross_Pay_Last_Paycheck	2242.020	1
## 108	128	129	Gross_FRS_Contribution	44061.785	1
## 109	130	131	Age	80.000	1
## 110	132	133	Gross_Year_To_Date	45812.135	1
## 111	134	135	yrs_residence	3.500	1
## 112	0	0	<NA>	0.000	-1
## 113	0	0	<NA>	0.000	-1
## 114	136	137	Gross_FRS_Contribution	50760.250	1
## 115	138	139	marital_status	3.500	1
## 116	140	141	marital_status	3.500	1
## 117	142	143	Age	85.000	1
## 118	0	0	<NA>	0.000	-1
## 119	0	0	<NA>	0.000	-1
## 120	144	145	yrs_residence	3.500	1
## 121	146	147	yrs_residence	3.500	1
## 122	0	0	<NA>	0.000	-1
## 123	0	0	<NA>	0.000	-1
## 124	0	0	<NA>	0.000	-1
## 125	0	0	<NA>	0.000	-1
## 126	0	0	<NA>	0.000	-1
## 127	0	0	<NA>	0.000	-1
## 128	148	149	marital_status	2.500	1
## 129	150	151	Annual.Salary	51487.670	1
## 130	0	0	<NA>	0.000	-1
## 131	0	0	<NA>	0.000	-1
## 132	152	153	Age	94.000	1
## 133	0	0	<NA>	0.000	-1
## 134	0	0	<NA>	0.000	-1

## 135	154	155	Gross_FRS_Contribution	44313.225	1
## 136	156	157	Gross_FRS_Contribution	50604.480	1
## 137	158	159	Age	101.500	1
## 138	160	161	yrs_residence	3.500	1
## 139	162	163	yrs_residence	3.500	1
## 140	164	165	yrs_residence	3.500	1
## 141	0	0	<NA>	0.000	-1
## 142	166	167	yrs_residence	3.500	1
## 143	0	0	<NA>	0.000	-1
## 144	0	0	<NA>	0.000	-1
## 145	0	0	<NA>	0.000	-1
## 146	0	0	<NA>	0.000	-1
## 147	0	0	<NA>	0.000	-1
## 148	168	169	Gross_Pay_Last_Paycheck	2334.380	1
## 149	170	171	Age	55.000	1
## 150	172	173	Age	96.500	1
## 151	174	175	yrs_residence	3.500	1
## 152	0	0	<NA>	0.000	-1
## 153	0	0	<NA>	0.000	-1
## 154	176	177	Age	72.500	1
## 155	0	0	<NA>	0.000	-1
## 156	178	179	yrs_residence	3.500	1
## 157	180	181	Gross_Pay_Last_Paycheck	3737.525	1
## 158	182	183	marital_status	2.500	1
## 159	184	185	yrs_residence	3.500	1
## 160	0	0	<NA>	0.000	-1
## 161	0	0	<NA>	0.000	-1
## 162	0	0	<NA>	0.000	-1
## 163	0	0	<NA>	0.000	-1
## 164	0	0	<NA>	0.000	-1
## 165	0	0	<NA>	0.000	-1
## 166	0	0	<NA>	0.000	-1
## 167	0	0	<NA>	0.000	-1
## 168	0	0	<NA>	0.000	-1
## 169	186	187	Gross_Pay_Last_Paycheck	2415.545	1
## 170	0	0	<NA>	0.000	-1
## 171	0	0	<NA>	0.000	-1
## 172	188	189	Age	38.000	1
## 173	0	0	<NA>	0.000	-1
## 174	0	0	<NA>	0.000	-1
## 175	0	0	<NA>	0.000	-1
## 176	0	0	<NA>	0.000	-1
## 177	0	0	<NA>	0.000	-1
## 178	0	0	<NA>	0.000	-1
## 179	0	0	<NA>	0.000	-1
## 180	190	191	Gross_FRS_Contribution	50703.810	1
## 181	0	0	<NA>	0.000	-1
## 182	192	193	Age	83.500	1
## 183	194	195	Annual.Salary	50460.800	1
## 184	0	0	<NA>	0.000	-1
## 185	0	0	<NA>	0.000	-1
## 186	0	0	<NA>	0.000	-1
## 187	0	0	<NA>	0.000	-1
## 188	0	0	<NA>	0.000	-1

## 189	196	197	Gross_Pay_Last_Paycheck	2534.520	1
## 190	198	199	Age	74.500	1
## 191	0	0	<NA>	0.000	-1
## 192	200	201	Annual.Salary	132045.030	1
## 193	202	203	Gross_FRS_Contribution	112887.560	1
## 194	204	205	yrs_residence	3.500	1
## 195	206	207	Annual.Salary	145809.690	1
## 196	208	209	Gross_Year_To_Date	50168.620	1
## 197	210	211	yrs_residence	3.500	1
## 198	212	213	Age	72.000	1
## 199	0	0	<NA>	0.000	-1
## 200	214	215	Age	81.500	1
## 201	216	217	Gross_FRS_Contribution	106766.025	1
## 202	218	219	Gross_FRS_Contribution	112108.800	1
## 203	220	221	Age	91.500	1
## 204	0	0	<NA>	0.000	-1
## 205	0	0	<NA>	0.000	-1
## 206	222	223	yrs_residence	3.500	1
## 207	224	225	Gross_FRS_Contribution	96391.345	1
## 208	226	227	Gross_Year_To_Date	49791.595	1
## 209	228	229	Gross_Year_To_Date	51087.680	1
## 210	0	0	<NA>	0.000	-1
## 211	0	0	<NA>	0.000	-1
## 212	230	231	yrs_residence	3.500	1
## 213	0	0	<NA>	0.000	-1
## 214	232	233	Gross_Pay_Last_Paycheck	9248.450	1
## 215	234	235	Gross_Pay_Last_Paycheck	2828.930	1
## 216	236	237	yrs_residence	3.500	1
## 217	238	239	Age	82.000	1
## 218	240	241	Gross_Year_To_Date	69889.030	1
## 219	0	0	<NA>	0.000	-1
## 220	242	243	Gross_FRS_Contribution	113594.045	1
## 221	244	245	Gross_Pay_Last_Paycheck	5011.430	1
## 222	0	0	<NA>	0.000	-1
## 223	0	0	<NA>	0.000	-1
## 224	246	247	Gross_Year_To_Date	80548.110	1
## 225	248	249	yrs_residence	3.500	1
## 226	250	251	Age	41.500	1
## 227	0	0	<NA>	0.000	-1
## 228	252	253	Gross_FRS_Contribution	49464.575	1
## 229	254	255	yrs_residence	3.500	1
## 230	0	0	<NA>	0.000	-1
## 231	0	0	<NA>	0.000	-1
## 232	256	257	Age	62.500	1
## 233	258	259	yrs_residence	3.500	1
## 234	0	0	<NA>	0.000	-1
## 235	260	261	Annual.Salary	130624.260	1
## 236	0	0	<NA>	0.000	-1
## 237	0	0	<NA>	0.000	-1
## 238	262	263	yrs_residence	3.500	1
## 239	0	0	<NA>	0.000	-1
## 240	264	265	Annual.Salary	83875.480	1
## 241	266	267	Annual.Salary	112704.670	1
## 242	0	0	<NA>	0.000	-1

## 243	0	0	<NA>	0.000	-1
## 244	0	0	<NA>	0.000	-1
## 245	268	269	Age	96.500	1
## 246	0	0	<NA>	0.000	-1
## 247	270	271	yrs_residence	3.500	1
## 248	0	0	<NA>	0.000	-1
## 249	0	0	<NA>	0.000	-1
## 250	0	0	<NA>	0.000	-1
## 251	272	273	Gross_Pay_Last_Paycheck	2340.540	1
## 252	274	275	Annual.Salary	51412.790	1
## 253	0	0	<NA>	0.000	-1
## 254	0	0	<NA>	0.000	-1
## 255	0	0	<NA>	0.000	-1
## 256	276	277	Gross_FRS_Contribution	61162.370	1
## 257	278	279	yrs_residence	3.500	1
## 258	0	0	<NA>	0.000	-1
## 259	0	0	<NA>	0.000	-1
## 260	280	281	Annual.Salary	113597.510	1
## 261	0	0	<NA>	0.000	-1
## 262	0	0	<NA>	0.000	-1
## 263	0	0	<NA>	0.000	-1
## 264	282	283	Gross_Year_To_Date	65698.770	1
## 265	284	285	Gross_FRS_Contribution	66611.580	1
## 266	286	287	Age	85.500	1
## 267	288	289	yrs_residence	3.500	1
## 268	290	291	yrs_residence	3.500	1
## 269	0	0	<NA>	0.000	-1
## 270	0	0	<NA>	0.000	-1
## 271	0	0	<NA>	0.000	-1
## 272	292	293	yrs_residence	3.500	1
## 273	294	295	Annual.Salary	51435.800	1
## 274	296	297	yrs_residence	3.500	1
## 275	0	0	<NA>	0.000	-1
## 276	298	299	Age	41.500	1
## 277	300	301	yrs_residence	3.500	1
## 278	0	0	<NA>	0.000	-1
## 279	0	0	<NA>	0.000	-1
## 280	302	303	Gross_FRS_Contribution	57058.210	1
## 281	304	305	yrs_residence	3.500	1
## 282	306	307	Gross_Year_To_Date	55292.560	1
## 283	0	0	<NA>	0.000	-1
## 284	308	309	Gross_Pay_Last_Paycheck	4661.865	1
## 285	310	311	yrs_residence	3.000	1
## 286	312	313	Gross_Pay_Last_Paycheck	4665.545	1
## 287	314	315	Gross_FRS_Contribution	94782.680	1
## 288	0	0	<NA>	0.000	-1
## 289	0	0	<NA>	0.000	-1
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## 297	0	0	<NA>	0.000	-1
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## 299	318	319	Annual.Salary	63240.450	1
## 300	0	0	<NA>	0.000	-1
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## 306	322	323	yrs_residence	3.500	1
## 307	324	325	Age	90.500	1
## 308	326	327	yrs_residence	3.000	1
## 309	0	0	<NA>	0.000	-1
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## 312	328	329	Annual.Salary	87569.560	1
## 313	330	331	Gross_FRS_Contribution	94707.685	1
## 314	332	333	Gross_Pay_Last_Paycheck	5026.180	1
## 315	0	0	<NA>	0.000	-1
## 316	0	0	<NA>	0.000	-1
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## 318	334	335	Age	61.500	1
## 319	336	337	Gross_FRS_Contribution	60971.450	1
## 320	0	0	<NA>	0.000	-1
## 321	0	0	<NA>	0.000	-1
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## 324	338	339	Gross_FRS_Contribution	63627.365	1
## 325	340	341	Gross_FRS_Contribution	62201.665	1
## 326	0	0	<NA>	0.000	-1
## 327	0	0	<NA>	0.000	-1
## 328	342	343	Gross_FRS_Contribution	68842.030	1
## 329	344	345	yrs_residence	3.500	1
## 330	346	347	Annual.Salary	71954.350	1
## 331	348	349	yrs_residence	3.000	1
## 332	350	351	Gross_FRS_Contribution	93889.445	1
## 333	352	353	Age	95.500	1
## 334	354	355	Age	57.500	1
## 335	0	0	<NA>	0.000	-1
## 336	356	357	Gross_Year_To_Date	53073.210	1
## 337	0	0	<NA>	0.000	-1
## 338	358	359	Gross_FRS_Contribution	60426.265	1
## 339	0	0	<NA>	0.000	-1
## 340	360	361	Gross_FRS_Contribution	59376.980	1
## 341	362	363	Gross_Year_To_Date	65293.230	1
## 342	0	0	<NA>	0.000	-1
## 343	364	365	Annual.Salary	85776.470	1
## 344	0	0	<NA>	0.000	-1
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## 346	366	367	Annual.Salary	58577.220	1
## 347	368	369	Gross_Year_To_Date	85186.085	1
## 348	0	0	<NA>	0.000	-1
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## 350	370	371	Gross_Year_To_Date	93892.470	1

## 351	372	373	yrs_residence	3.500	1
## 352	0	0	<NA>	0.000	-1
## 353	374	375	Gross_Pay_Last_Paycheck	6180.520	1
## 354	376	377	Gross_Year_To_Date	58207.840	1
## 355	378	379	yrs_residence	3.500	1
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## 357	380	381	yrs_residence	3.500	1
## 358	382	383	Age	88.500	1
## 359	384	385	yrs_residence	3.500	1
## 360	386	387	Gross_Year_To_Date	60840.085	1
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## 362	390	391	Gross_FRS_Contribution	62437.615	1
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## 370	396	397	Gross_FRS_Contribution	71811.690	1
## 371	398	399	yrs_residence	3.500	1
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## 376	402	403	Gross_FRS_Contribution	55778.140	1
## 377	404	405	Gross_Year_To_Date	60015.545	1
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## 383	408	409	Gross_Year_To_Date	62149.890	1
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## 403	426	427	Annual.Salary	59375.030	1
## 404	428	429	Annual.Salary	50648.000	1

## 405	430	431	Gross_Pay_Last_Paycheck	2995.020	1
## 406	432	433	Gross_Year_To_Date	56870.900	1
## 407	434	435	Annual.Salary	55089.710	1
## 408	436	437	Gross_Pay_Last_Paycheck	2837.520	1
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## 420	448	449	Annual.Salary	72511.400	1
## 421	450	451	yrs_residence	3.500	1
## 422	452	453	Gross_Pay_Last_Paycheck	3322.385	1
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## 431	464	465	Gross_FRS_Contribution	58632.685	1
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## 435	470	471	yrs_residence	3.000	1
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## 448	476	477	yrs_residence	3.500	1
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## 489	500	501	yrs_residence	3.500	1
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## 470	0
## 471	1
## 472	<NA>
## 473	<NA>
## 474	0


```

## 475      <NA>
## 476      0
## 477      1
## 478      0
## 479      1
## 480      0
## 481      1
## 482      0
## 483      <NA>
## 484      0
## 485      1
## 486      0
## 487      1
## 488      <NA>
## 489      <NA>
## 490      <NA>
## 491      <NA>
## 492      0
## 493      1
## 494      <NA>
## 495      <NA>
## 496      0
## 497      1
## 498      1
## 499      0
## 500      0
## 501      1
## 502      1
## 503      0
## 504      0
## 505      1
## 506      <NA>
## 507      <NA>
## 508      <NA>
## 509      <NA>
## 510      0
## 511      <NA>
## 512      <NA>
## 513      0
## 514      <NA>
## 515      0
## 516      1
## 517      0
## 518      1
## 519      0
## 520      1
## 521      0
## 522      0
## 523      1

```

Imagine you are a bank manager, and you want to decide which customers can get a loan. Instead of doing this manually, you build a model (the decision tree) to make the decision for you. The decision tree works by asking a series of yes/no questions about each customer. For example:

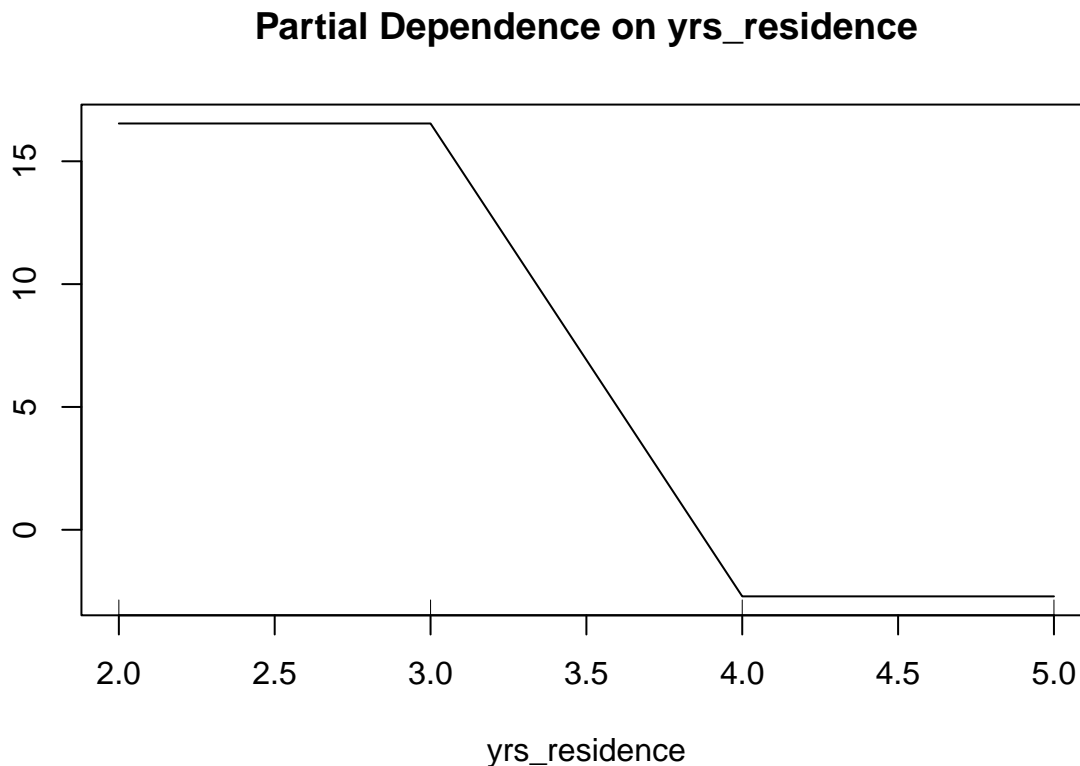
1. Does the customer earn more than R50,000 annually? If yes, they move to the left branch; if no, they

2. Has the customer lived in their current residence for more than 3 years? Another yes/no question.
3. Is their annual gross income more than R45,000? Another split.

At the end of this question-and-answer game, the tree makes a decision: “eligible” or “not eligible.” Each split is chosen because it helps the model make the best decision based on past data.

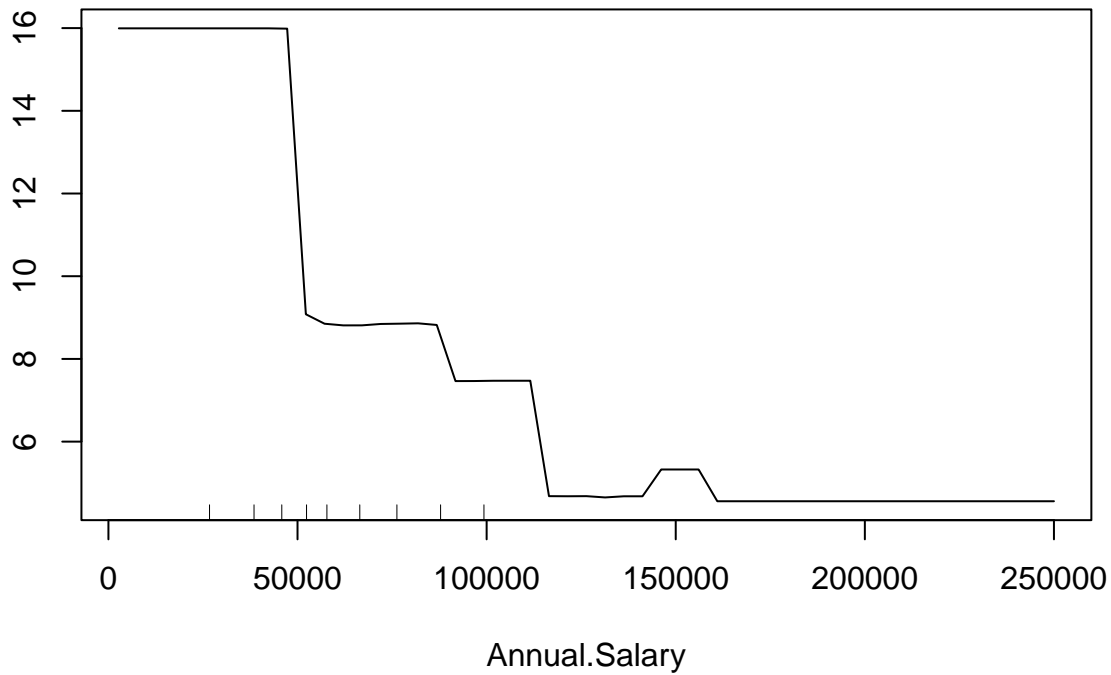
Create a partial dependence plot

```
partialPlot(rf_model, trainData, yrs_residence, main = "Partial Dependence on yrs_residence")
```



```
# Create a partial dependence plot for 'Annual.Salary'  
partialPlot(rf_model, trainData, Annual.Salary, main = "Partial Dependence on Annual.Salary")
```

Partial Dependence on Annual.Salary



PDPs illustrate how changes in a feature impact the predicted probability of an outcome while holding other features constant

a PDP for yrs_residence might show how the probability of being classified as “eligible” changes as the yrs_residence increases.

If the plot slopes upward, it means that as yrs_residence increases, the probability of a customer being eligible increases.

A flat section in the plot suggests that beyond a certain point, changes in that feature don’t significantly impact the prediction.

PDPs can also reveal non-linear effects. For example, eligibility might increase sharply with Annual.Salary up to a certain threshold, then level off.