Project Creditworthiness

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Step 1: Business and Data Understanding

What decisions needs to be made?

Determining whether customers are creditworthy to give a loan to.

What data is needed to inform those decisions?

- Data set of past applications for training models:
  - Outcome: Credit-Application-Result.
  - Potention predictors: Duration_of_Credit_Month, Credit_Amount, Age_years, Instalment_per_cent, Most_valuable_available_asset, Type_of_apartment, and so on.
- New data set (without outcome variable) to apply the chosen model and make decisions.

What kind of model (Continuous, Binary, Non-Binary, Time-Series) do we need to use to help make these decisions?

Binary model.

Step 2: Building the Training Set

After importing, the data set were formatted as suggested.

```
## Rows: 500
## Columns: 20
## $ Credit_Application_Result         <chr> "Creditworthy", "Creditworthy", "...
## $ Account_Balance                   <chr> "Some Balance", "Some Balance", "...
## $ Duration_of_Credit_Month          <int> 4, 4, 4, 4, 6, 6, 6, 6, 6, 6, 6, ...
## $ Payment_Status_of_Previous_Credit <chr> "Paid Up", "Paid Up", "No Problem...
## $ Purpose                           <chr> "Other", "Home Related", "Home Re...
## $ Credit_Amount                     <int> 1494, 1494, 1544, 3380, 343, 362,...
## $ Value_Savings_Stocks              <chr> "£100-£1000", "£100-£1000", "None...
## $ Length_of_current_employment      <chr> "< 1yr", "< 1yr", "1-4 yrs", "1-4...
## $ Instalment_per_cent               <int> 1, 1, 2, 1, 4, 4, 4, 3, 3, 2, 3, ...
## $ Guarantors                        <chr> "None", "None", "None", "None", "...
## $ Duration_in_Current_address       <int> 2, 2, 1, 1, 1, NA, NA, NA, 3, 4, ...
## $ Most_valuable_available_asset     <int> 1, 1, 1, 1, 1, 3, 2, 2, 1, 1, 1, ...
## $ Age_years                         <int> NA, 29, 42, 37, 27, 52, 24, 22, 2...
## $ Concurrent_Credits                <chr> "Other Banks/Depts", "Other Banks...
## $ Type_of_apartment                 <int> 2, 2, 2, 2, 2, 2, 1, 2, 2, 1, 2, ...
```

```
## $ No_of_Credits_at_this_Bank        <chr> "1", "1", "More than 1", "1", "1"...
## $ Occupation                        <int> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, ...
## $ No_of_dependents                  <int> 2, 2, 2, 2, 1, 1, 2, 1, 1, 1, 1, ...
## $ Telephone                         <int> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, ...
## $ Foreign_Worker                    <int> 2, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, ...
```

Identifying and imputing missing data

The number of missing values in each field:

```
##                                field no_of_missing
## 1          Credit_Application_Result             0
## 2                    Account_Balance             0
## 3           Duration_of_Credit_Month             0
## 4  Payment_Status_of_Previous_Credit             0
## 5                            Purpose             0
## 6                      Credit_Amount             0
## 7                Value_Savings_Stocks             0
## 8        Length_of_current_employment             0
## 9                 Instalment_per_cent             0
## 10                        Guarantors             0
## 11        Duration_in_Current_address           344
## 12      Most_valuable_available_asset             0
## 13                         Age_years            12
## 14                  Concurrent_Credits             0
## 15                   Type_of_apartment             0
## 16          No_of_Credits_at_this_Bank             0
## 17                          Occupation             0
## 18                    No_of_dependents             0
## 19                           Telephone             0
## 20                      Foreign_Worker             0
```

`Duration_in_Current_address` has 344 missing values so I dropped it. `Age_years` has 12 missing values so I imputed it by median.

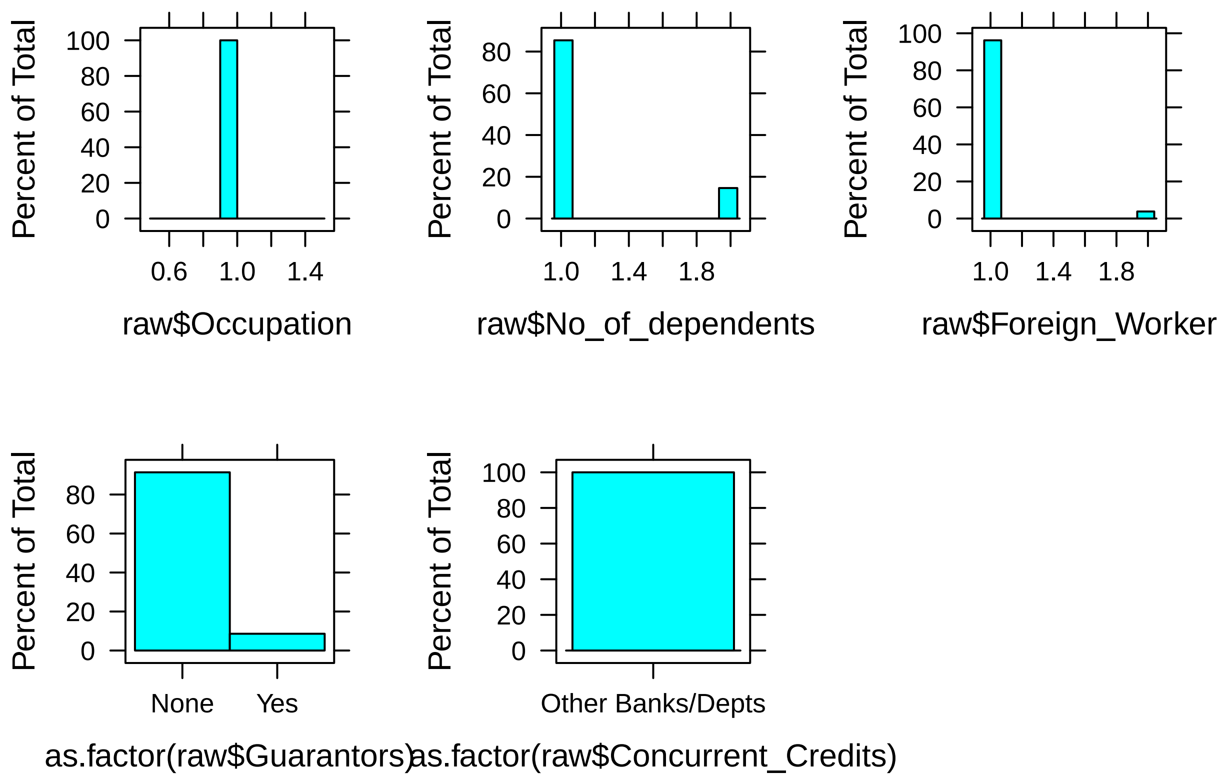
```
## [1] 35.574
```

Identifying low-variability fields and removing them

Frequency table and histogram of low-variability fields:

```
## [[1]]
##   Occupation   n
## 1          1 500
##
## [[2]]
##   No_of_dependents   n
## 1                1 427
## 2                2  73
##
## [[3]]
##   Foreign_Worker   n
```

```
## 1              1 481
## 2              2  19
##
## [[4]]
##   Guarantors   n
## 1       None 457
## 2        Yes  43
##
## [[5]]
##   Concurrent_Credits   n
## 1  Other Banks/Depts 500
```



After removing those fields plus `Telephone`, no high correlation was detected among numeric fields:

```
##                              Duration_of_Credit_Month Credit_Amount
## Duration_of_Credit_Month                   1.00000000    0.57397971
## Credit_Amount                              0.57397971    1.00000000
## Age_years                                 -0.06419695    0.06931589
## Instalment_per_cent                        0.06810553   -0.28885153
## Most_valuable_available_asset              0.29985487    0.32554538
## Type_of_apartment                          0.15251629    0.17007119
##                                Age_years Instalment_per_cent
## Duration_of_Credit_Month     -0.06419695          0.06810553
## Credit_Amount                 0.06931589         -0.28885153
## Age_years                     1.00000000          0.03926967
## Instalment_per_cent           0.03926967          1.00000000
```

```
## Most_valuable_available_asset  0.08623342          0.08149260
## Type_of_apartment              0.32935038          0.07453322
##                               Most_valuable_available_asset Type_of_apartment
## Duration_of_Credit_Month                         0.29985487        0.15251629
## Credit_Amount                                    0.32554538        0.17007119
## Age_years                                        0.08623342        0.32935038
## Instalment_per_cent                              0.08149260        0.07453322
## Most_valuable_available_asset                    1.00000000        0.37310079
## Type_of_apartment                                0.37310079        1.00000000
```

The final data set has 13 columns

```
## Rows: 500
## Columns: 13
## $ Duration_of_Credit_Month          <int> 4, 4, 4, 4, 6, 6, 6, 6, 6, 6, 6, ...
## $ Credit_Amount                     <int> 1494, 1494, 1544, 3380, 343, 362,...
## $ Age_years                         <dbl> 33, 29, 42, 37, 27, 52, 24, 22, 2...
## $ Instalment_per_cent               <int> 1, 1, 2, 1, 4, 4, 4, 3, 3, 2, 3, ...
## $ Most_valuable_available_asset     <int> 1, 1, 1, 1, 1, 3, 2, 2, 1, 1, 1, ...
## $ Type_of_apartment                 <int> 2, 2, 2, 2, 2, 2, 1, 2, 2, 1, 2, ...
## $ Credit_Application_Result         <fct> Creditworthy, Creditworthy, Credi...
## $ Account_Balance                   <fct> Some Balance, Some Balance, Some ...
## $ Payment_Status_of_Previous_Credit <fct> Paid Up, Paid Up, No Problems (in...
## $ Purpose                           <fct> Other, Home Related, Home Related...
## $ Value_Savings_Stocks              <fct> £100-£1000, £100-£1000, None, Non...
## $ Length_of_current_employment      <fct> < 1yr, < 1yr, 1-4 yrs, 1-4 yrs, <...
## $ No_of_Credits_at_this_Bank        <fct> 1, 1, More than 1, 1, 1, More tha...
```

Step 3: Train your Classification Models

Create Estimation and Validation samples

Confusion matrices

```
## Confusion Matrix and Statistics
##
##                   Reference
## Prediction         Creditworthy Non-Creditworthy
##   Creditworthy              104               22
##   Non-Creditworthy            3               20
##
##                Accuracy : 0.8322
##                  95% CI : (0.7624, 0.8884)
##     No Information Rate : 0.7181
##     P-Value [Acc > NIR] : 0.0008381
##
##                   Kappa : 0.5195
##
##  Mcnemar's Test P-Value : 0.0003182
##
##             Sensitivity : 0.9720
##             Specificity : 0.4762
##          Pos Pred Value : 0.8254
```

```
##          Neg Pred Value : 0.8696
##              Prevalence : 0.7181
##          Detection Rate : 0.6980
##    Detection Prevalence : 0.8456
##       Balanced Accuracy : 0.7241
##
##        'Positive' Class : Creditworthy
##
```

```
## Confusion Matrix and Statistics
##
##                   Reference
## Prediction         Creditworthy Non-Creditworthy
##   Creditworthy              103               23
##   Non-Creditworthy            4               19
##
##                Accuracy : 0.8188
##                  95% CI : (0.7474, 0.8771)
##     No Information Rate : 0.7181
##     P-Value [Acc > NIR] : 0.003077
##
##                   Kappa : 0.4811
##
##  Mcnemar's Test P-Value : 0.000532
##
##             Sensitivity : 0.9626
##             Specificity : 0.4524
##          Pos Pred Value : 0.8175
##          Neg Pred Value : 0.8261
##              Prevalence : 0.7181
##          Detection Rate : 0.6913
##    Detection Prevalence : 0.8456
##       Balanced Accuracy : 0.7075
##
##        'Positive' Class : Creditworthy
##
```

```
## Confusion Matrix and Statistics
##
##                   Reference
## Prediction         Creditworthy Non-Creditworthy
##   Creditworthy              106               32
##   Non-Creditworthy            1               10
##
##                Accuracy : 0.7785
##                  95% CI : (0.7033, 0.8424)
##     No Information Rate : 0.7181
##     P-Value [Acc > NIR] : 0.05832
##
##                   Kappa : 0.2949
##
##  Mcnemar's Test P-Value : 1.767e-07
##
##             Sensitivity : 0.9907
```

```
##             Specificity : 0.2381
##          Pos Pred Value : 0.7681
##          Neg Pred Value : 0.9091
##              Prevalence : 0.7181
##          Detection Rate : 0.7114
##    Detection Prevalence : 0.9262
##       Balanced Accuracy : 0.6144
##
##        'Positive' Class : Creditworthy
##
```

```
## Confusion Matrix and Statistics
##
##                   Reference
## Prediction         Creditworthy Non-Creditworthy
##   Creditworthy              102               23
##   Non-Creditworthy            5               19
##
##                Accuracy : 0.8121
##                  95% CI : (0.74, 0.8713)
##     No Information Rate : 0.7181
##     P-Value [Acc > NIR] : 0.005532
##
##                   Kappa : 0.4664
##
##  Mcnemar's Test P-Value : 0.001315
##
##             Sensitivity : 0.9533
##             Specificity : 0.4524
##          Pos Pred Value : 0.8160
##          Neg Pred Value : 0.7917
##              Prevalence : 0.7181
##          Detection Rate : 0.6846
##    Detection Prevalence : 0.8389
##       Balanced Accuracy : 0.7028
##
##        'Positive' Class : Creditworthy
##
```

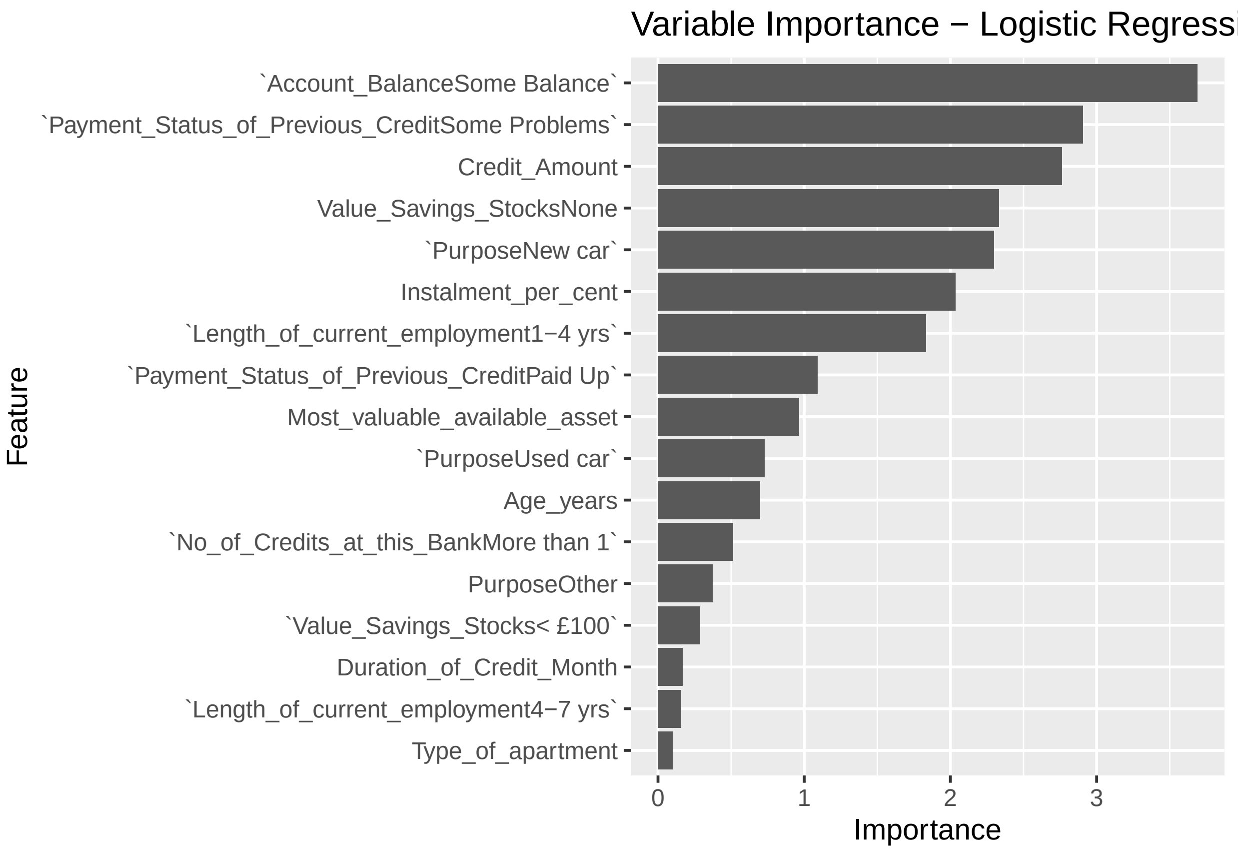
Overall accuracy

Among the 4 models, Logistic regression has the highest overall accuracy agains the Validation set (0.83). The bias was not observed in Logistic regression, Random forest, and Boosted tree model considering PPV and NPV.

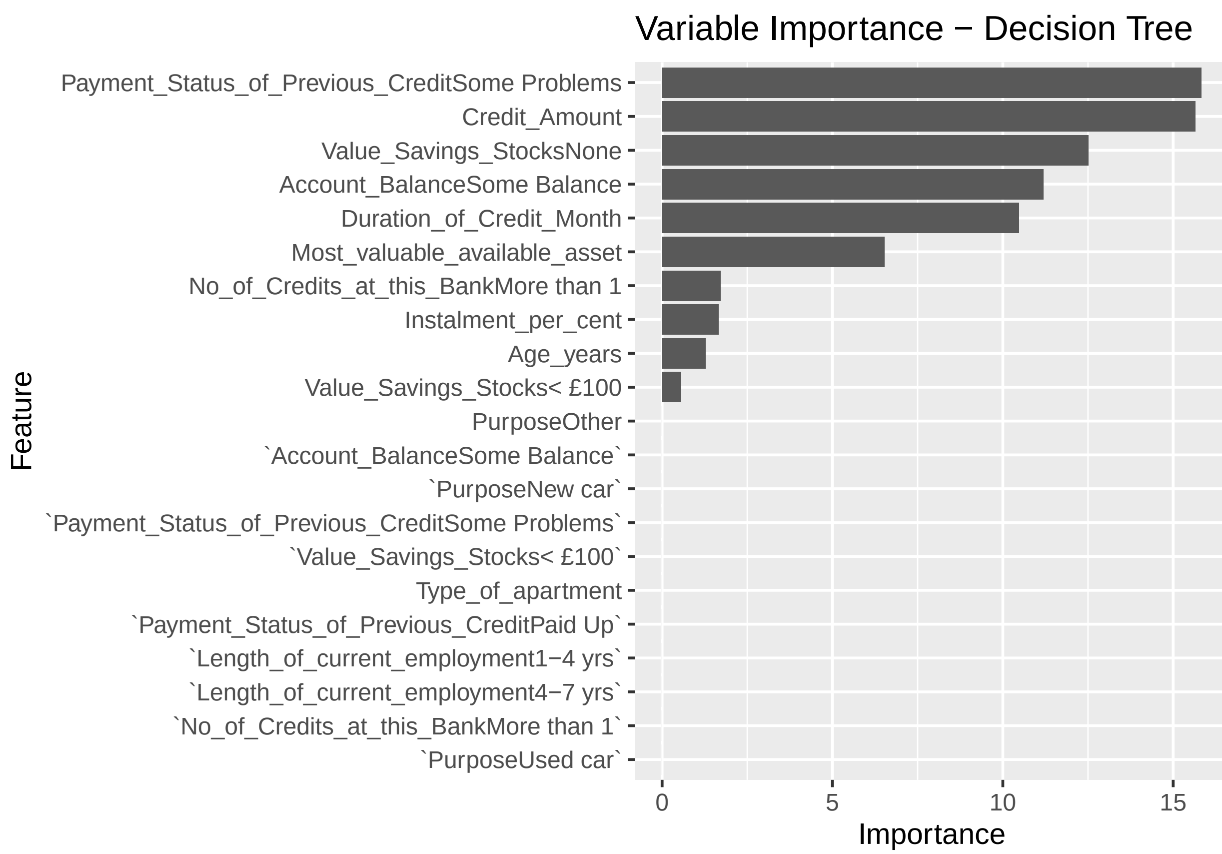
```
##                       lr      tree    forest   boosted
## Accuracy_train 0.7692308 0.7806268 0.8860399 0.7948718
## Accuracy_test  0.8322148 0.8187919 0.7785235 0.8120805
## PPV            0.8253968 0.8174603 0.7681159 0.8160000
## NPV            0.8695652 0.8260870 0.9090909 0.7916667
```

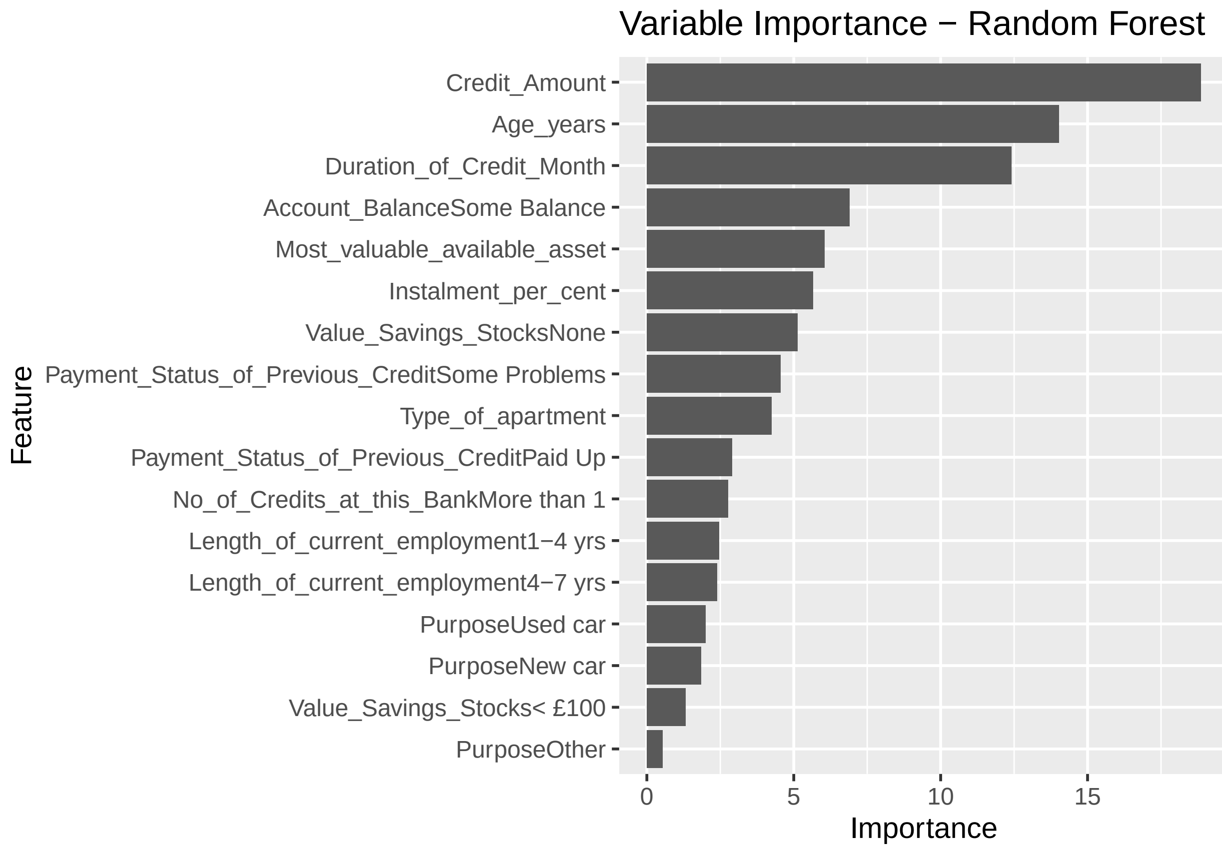
Plot variable importance

Most important predictors: - For Logistic regression: Account_Balance, Payment_Status_of_Previous_Credit, Credit_Amoun, Value_Savings_Stocks, Purpose, Instalment_per_cent. - For Decision tree: Payment_Status_of_Previous_Credit, Credit_Amount, Value_Savings_Stocks, Account_Balance, Duration_of_Credit_Month. - For Random forest: Credit_Amount, Age_years, Duration_of_Credit_Month. - For Boosted tree: Account_Balance, Value_Savings_Stocks, Paymen_Status_of_Previous_Credit, and Duration_of_Credit_Month are the 4 most important variables. The difference is not remarkable among the

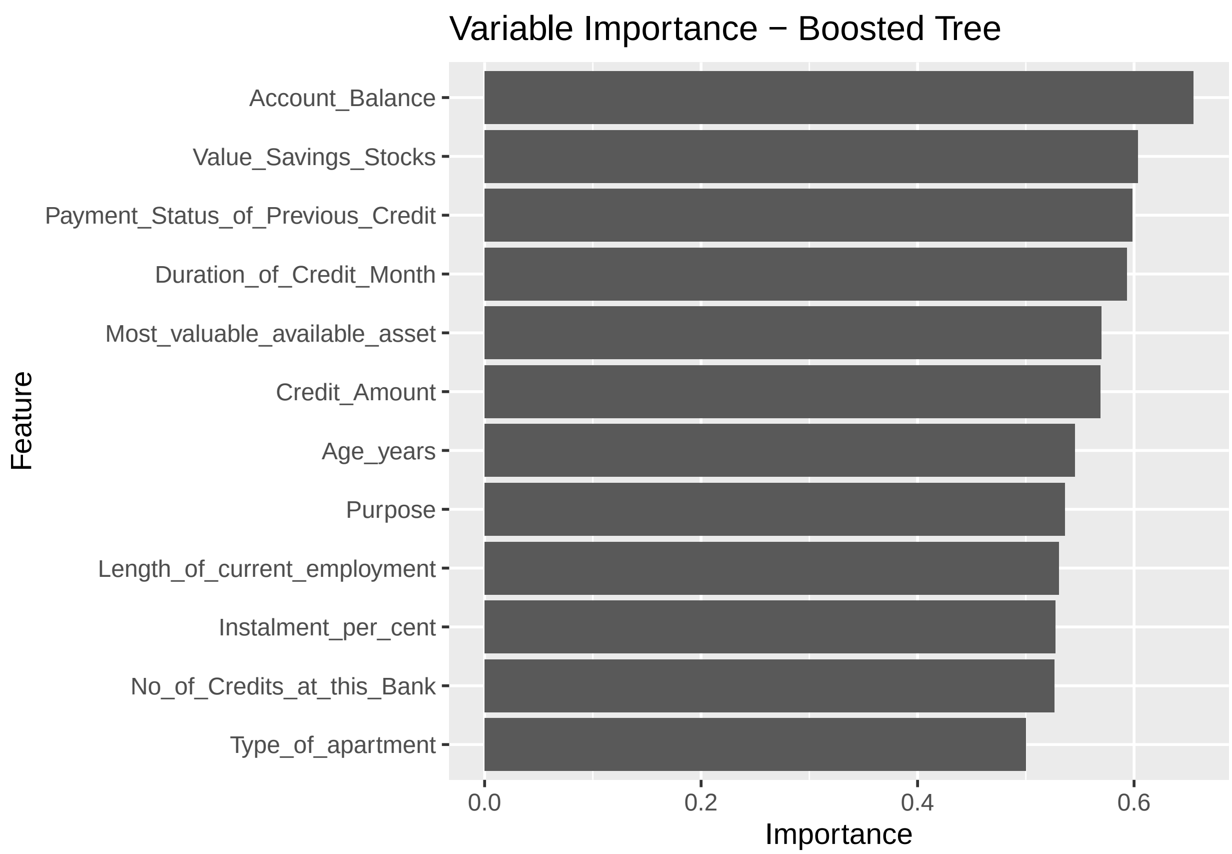


fields.


Variable Importance − Decision Tree
Payment_Status_of_Previous_CreditSome Problems
Credit_Amount
Value_Savings_StocksNone
Account_BalanceSome Balance
Duration_of_Credit_Month
Most_valuable_available_asset
No_of_Credits_at_this_BankMore than 1
Instalment_per_cent
Age_years
Value_Savings_Stocks< £100
PurposeOther
`Account_BalanceSome Balance`
`PurposeNew car`
`Payment_Status_of_Previous_CreditSome Problems`
`Value_Savings_Stocks< £100`
Type_of_apartment
`Payment_Status_of_Previous_CreditPaid Up`
`Length_of_current_employment1−4 yrs`
`Length_of_current_employment4−7 yrs`
`No_of_Credits_at_this_BankMore than 1`
`PurposeUsed car`
Feature
0
5
10
15
Importance



Variable Importance − Random Forest
Credit_Amount
Age_years
Duration_of_Credit_Month
Account_BalanceSome Balance
Most_valuable_available_asset
Instalment_per_cent
Value_Savings_StocksNone
Payment_Status_of_Previous_CreditSome Problems
Type_of_apartment
Payment_Status_of_Previous_CreditPaid Up
No_of_Credits_at_this_BankMore than 1
Length_of_current_employment1−4 yrs
Length_of_current_employment4−7 yrs
PurposeUsed car
PurposeNew car
Value_Savings_Stocks< £100
PurposeOther
Feature
0
5
10
15
Importance



Step 4: Writeup

Accuracy table

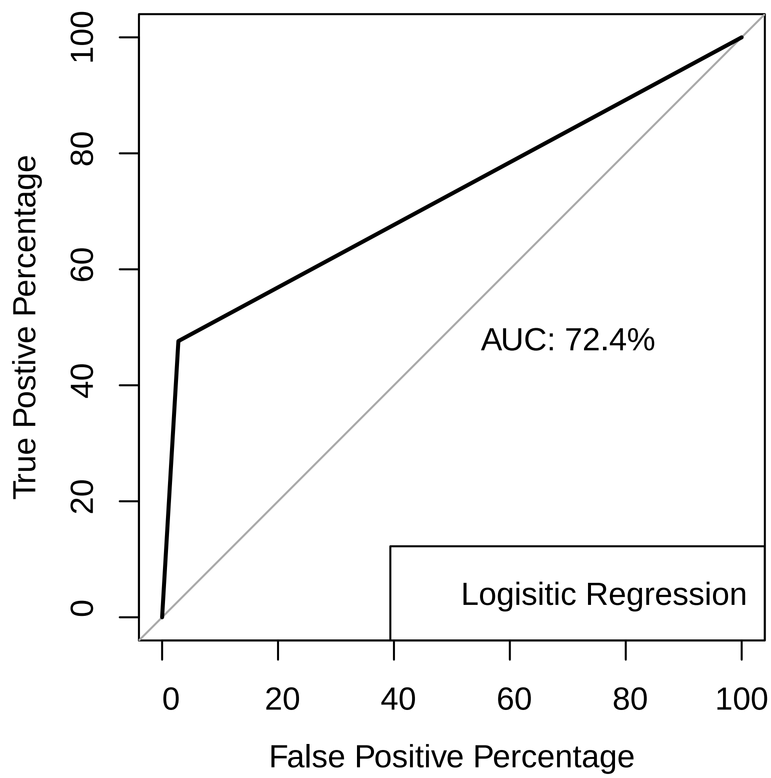
```
##                        lr      tree    forest   boosted
## Accuracy_train 0.7692308 0.7806268 0.8860399 0.7948718
## Accuracy_test  0.8322148 0.8187919 0.7785235 0.8120805
## PPV            0.8253968 0.8174603 0.7681159 0.8160000
## NPV            0.8695652 0.8260870 0.9090909 0.7916667
```

Plot ROCs

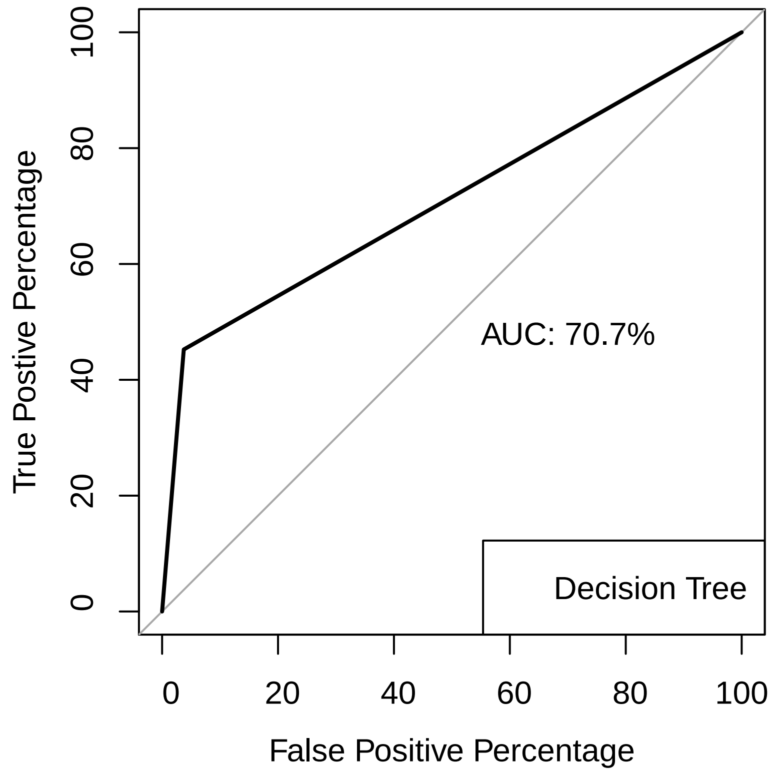
```
## Setting levels: control = 1, case = 2
```

```
## Setting direction: controls < cases
```

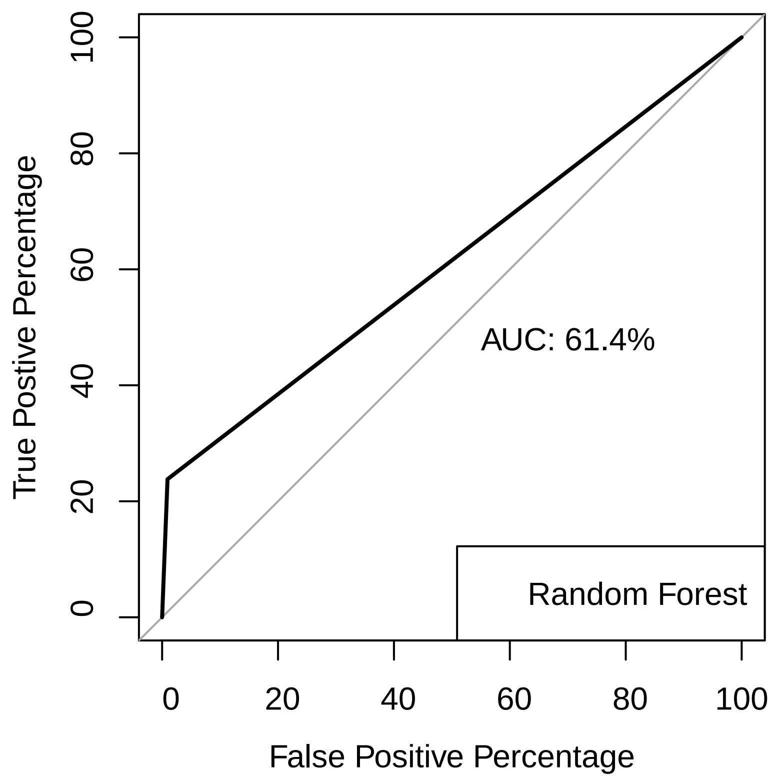
```
##
## Call:
## roc.default(response = as.numeric(test$Credit_Application_Result),     predictor = as.numeric(y_hat1
##
## Data: as.numeric(y_hat1) in 107 controls (as.numeric(test$Credit_Application_Result) 1) < 42 cases (a
## Area under the curve: 72.41%
```



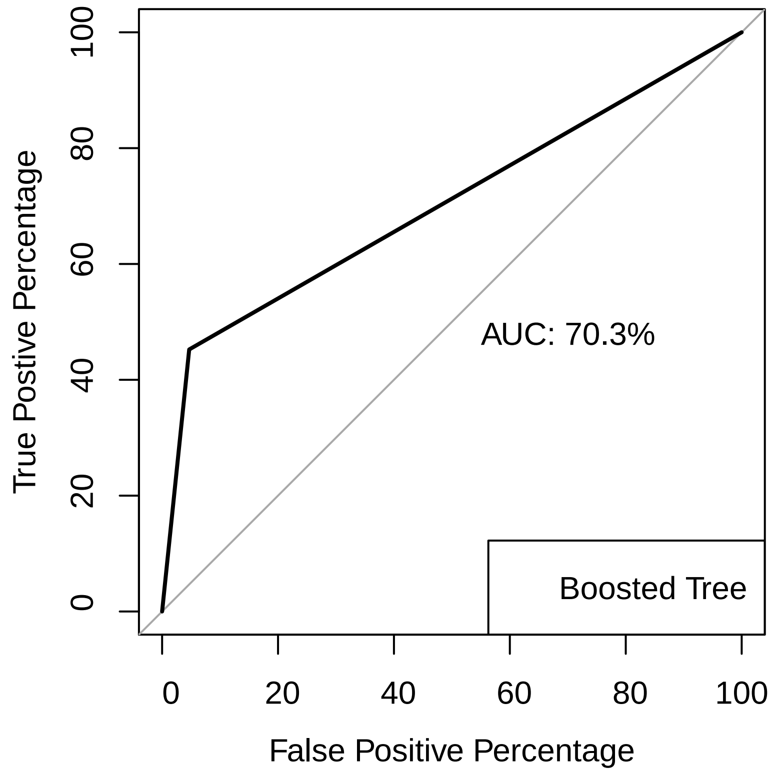

```
## Setting levels: control = 1, case = 2
## Setting direction: controls < cases
```




```
## Setting levels: control = 1, case = 2
## Setting direction: controls < cases
```




```
## Setting levels: control = 1, case = 2
## Setting direction: controls < cases
```



Logistic regresson model is not bias and has the highest overall accuracy against the Validation set. It is also has the most optimal ROC. Therefore, I choose to use logistic regression model. Applying the chosen model, the number of individuals are creditworthy is 413.

```
## [1] 413
```