Project: Creditworthiness

Complete each section. When you are ready, save your file as a PDF document and submit it here: https://classroom.udacity.com/nanodegrees/nd008/parts/11a7bf4c-2b69-47f3-9aec-108ce847f855/project

Step 1: Business and Data Understanding

Provide an explanation of the key decisions that need to be made. (250 word limit)

Key Decisions:

Answer these questions

- What decisions needs to be made?

The decision to be made is that we should decide if a person who wants a loan is creditworthy or not.

- What data is needed to inform those decisions?

We need to know the information about the people who applied for a loan before like their age, the reason which makes them take a loan, and how long have they employed.

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

As we want to decide if the person who applied for the loan is creditworthy or not creditworthy, so the model is binary due to there are two options.

Step 2: Building the Training Set

After visualizing the data by field summary tool

As we see above, Concurrent-Credits, Guarantors, Occupation, No-of-dependents, and Foreign-Worker are low variability. Duration-in-Current-address has many missing data and the Telephone is not relevant data. So, I removed these fields. Age-years has a few missing data, so I imputed by the median to ensure that is not affected by outliers.

Build your training set given the data provided to you. The data has been cleaned up for you already so you shouldn't ***need to convert any data fields to the appropriate data types.***

Here are some guidelines to help guide your data cleanup:

- For numerical data fields, are there any fields that highly-correlate with each other? The correlation should be at least .70 to be considered "high".
- Are there any missing data for each of the data fields? Fields with a lot of missing data should be removed
- Are there only a few values in a subset of your data field? Does the data field look very uniform (there is only one value for the entire field?). This is called "low variability" and

you should remove fields that have low variability. Refer to the "Tips" section to find examples of data fields with low-variability.

- Your clean data set should have 13 columns where the Average of **Age Years** should be 36 (rounded up)

Note: *For the sake of consistency in the data cleanup process, impute data using the median of the entire data field instead of removing a few data points. (100 word limit)*

Note: *For students using software other than Alteryx, please format each variable as:*

Variable	**Data Type**
Credit-Application-Result	String
Account-Balance	String
Duration-of-Credit-Month	Double
Payment-Status-of-Previous-Credit	String
Purpose	String
Credit-Amount	Double
Value-Savings-Stocks	String
Length-of-current-employment	String
Instalment-per-cent	Double
Guarantors	String
Duration-in-Current-address	Double
Most-valuable-available-asset	Double
Age-years	Double
Concurrent-Credits	String
Type-of-apartment	Double
No-of-Credits-at-this-Bank	String
Occupation	Double
No-of-dependents	Double
Telephone	Double
Foreign-Worker	Double

To achieve consistent results reviewers expect.

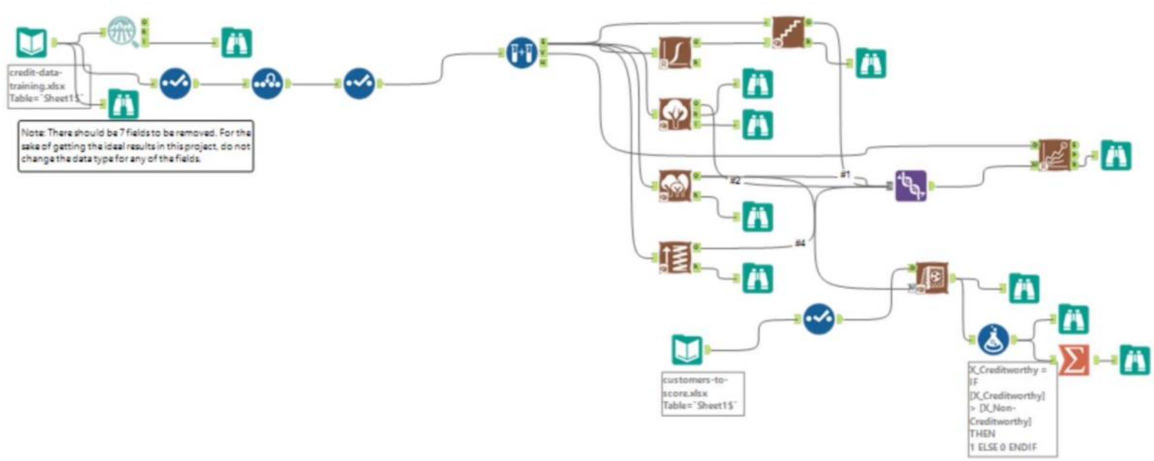
Answer this question:

- In your cleanup process, which fields did you remove or impute? Please justify why you removed or imputed these fields. Visualizations are encouraged.

Step 3: Train your Classification Models

First, create your Estimation and Validation samples where 70% of your dataset should go to Estimation and 30% of your entire dataset should be reserved for Validation. Set the Random Seed to 1.

Create all of the following models: Logistic Regression, Decision Tree, Forest Model, Boosted Model



As we see the workflow above, I built the required models: Logistic Regression, Decision Tree, Forest Model, and Boosted Tree.

*Answer these questions for **each model** you created:*

- Which predictor variables are significant or the most important? Please show the p-values or variable importance charts for all of your predictor variables.

Logistic Regression Model

Report for Logistic Regression Model LRM

Basic Summary

Call:

glm(formula = Credit.Application.Result ~ Account.Balance + Payment.Status.of.Previous.Credit + Purpose + Credit.Amount + Length.of.current.employment + Instalment.per.cent + Most.valuable.available.asset, family = binomial(logit), data = the.data)

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.289	-0.713	-0.448	0.722	2.454

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-2.9621914	6.837e-01	-4.3326	1e-05 ***
Account.BalanceSome Balance	-1.6053228	3.067e-01	-5.2344	1.65e-07 ***
Payment.Status.of.Previous.CreditPaid Up	0.2360857	2.977e-01	0.7930	0.42775
Payment.Status.of.Previous.CreditSome Problems	1.2154514	5.151e-01	2.3595	0.0183 *
PurposeNew car	-1.6993164	6.142e-01	-2.7668	0.00566 **
PurposeOther	-0.3257637	8.179e-01	-0.3983	0.69042
PurposeUsed car	-0.7645820	4.004e-01	-1.9096	0.05618 .
Credit.Amount	0.0001704	5.733e-05	2.9716	0.00296 **
Length.of.current.employment4-7 yrs	0.3127022	4.587e-01	0.6817	0.49545
Length.of.current.employment< 1yr	0.8125785	3.874e-01	2.0973	0.03596 *
Instalment.per.cent	0.3016731	1.350e-01	2.2340	0.02549 *
Most.valuable.available.asset	0.2650267	1.425e-01	1.8599	0.06289 .

Decision Tree Model

Summary Report for Decision Tree Model DTM

Call:

rpart(formula = Credit.Application.Result ~ Account.Balance + Duration.of.Credit.Month + Payment.Status.of.Previous.Credit + Purpose + Credit.Amount + Value.Savings.Stocks + Length.of.current.employment + Instalment.per.cent + Most.valuable.available.asset + Type.of.apartment + No.of.Credits.at.this.Bank + Age_years, data = the.data, minsplit = 20, minbucket = 7, usesurrogate = 2, xval = 10, maxdepth = 20, cp = 1e-05)

Model Summary

Variables actually used in tree construction:

[1] Account.Balance Duration.of.Credit.Month Purpose

[4] Value.Savings.Stocks

Root node error: 97/350 = 0.27714

n= 350

Pruning Table

Level	CP	Num Splits	Rel Error	X Error	X Std Dev
1	0.068729	0	1.00000	1.00000	0.086326
2	0.041237	3	0.79381	0.94845	0.084898
3	0.025773	4	0.75258	0.88660	0.083032

Leaf Summary

node), split, n, loss, yval, (yprob)

* denotes terminal node

1) root 350 97 Creditworthy (0.7228571 0.2771429)

2) Account.Balance=Some Balance 166 20 Creditworthy (0.8795181 0.1204819) *

3) Account.Balance=No Account 184 77 Creditworthy (0.5815217 0.4184783)

6) Duration.of.Credit.Month< 13 74 18 Creditworthy (0.7567568 0.2432432) *

7) Duration.of.Credit.Month>=13 110 51 Non-Creditworthy (0.4636364 0.5363636)

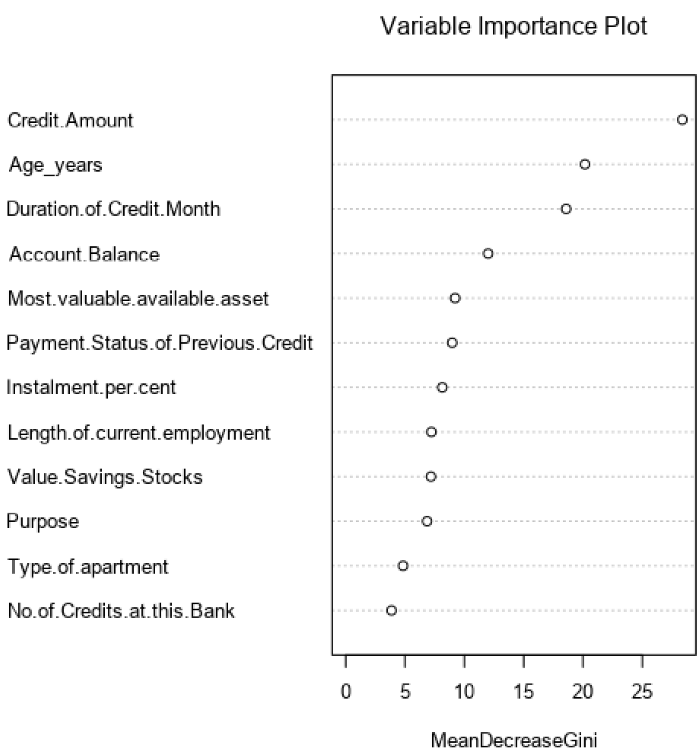
14) Value.Savings.Stocks=< £100,£100-£1000 34 11 Creditworthy (0.6764706 0.3235294) *

15) Value.Savings.Stocks=None 76 28 Non-Creditworthy (0.3684211 0.6315789)

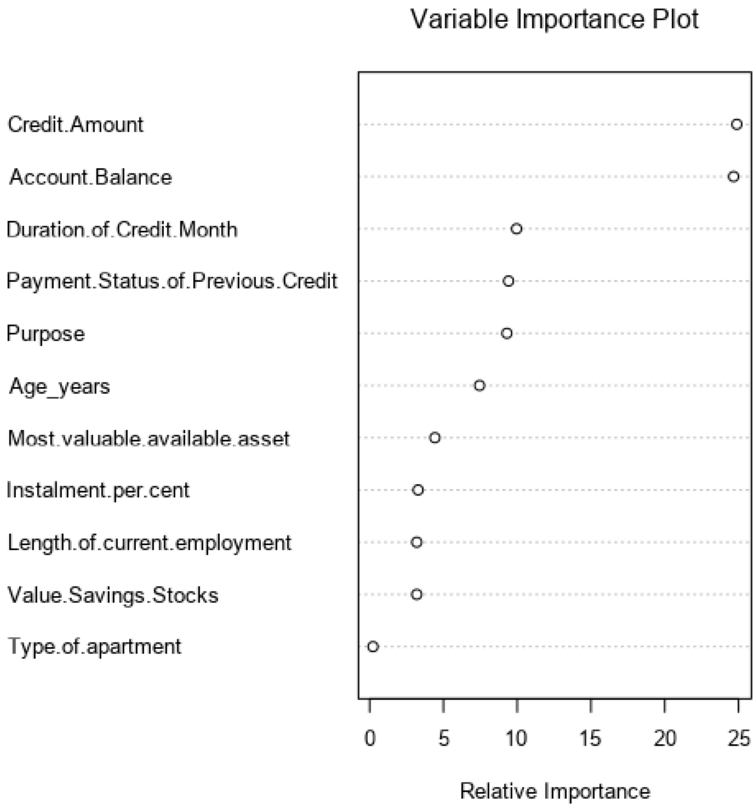
30) Purpose=New car 8 2 Creditworthy (0.7500000 0.2500000) *

31) Purpose=Home Related,Other,Used car 68 22 Non-Creditworthy (0.3235294 0.6764706) *

Forest Model



Boosted Model



From the report of models above, the significant of predictor variables for Logistic Regression Model is Account.BalanceSome Balance, Decision Tree Model is Account.Balance, Forest Model is Credit-Amount, and Boosted Tree Model is Credit-Amount.

- Validate your model against the Validation set. What was the overall percent accuracy? Show the confusion matrix. Are there any bias seen in the model's predictions?

Model	Accuracy
DTM	0.7467
FM	0.8000
BM	0.7867
LRM	0.7600

Confusion matrix of BM

	Actual_Creditworthy	Actual_Non-Creditworthy
Predicted_Creditworthy	101	28
Predicted_Non-Creditworthy	4	17

Confusion matrix of DTM

	Actual_Creditworthy	Actual_Non-Creditworthy
Predicted_Creditworthy	91	24
Predicted_Non-Creditworthy	14	21

Confusion matrix of FM

	Actual_Creditworthy	Actual_Non-Creditworthy
Predicted_Creditworthy	101	26
Predicted_Non-Creditworthy	4	19

Confusion matrix of LRM

	Actual_Creditworthy	Actual_Non-Creditworthy
Predicted_Creditworthy	92	23
Predicted_Non-Creditworthy	13	22

- There is bias in Boosted Tree Model prediction. It predicted the highest number of persons who are 28 persons as creditworthy and actually are non-creditworthy.
- Decision Tree Model predicted the highest number of persons who are 14 persons as non-creditworthy and are creditworthy.
- Forest Model predicted 26 persons as creditworthy and actually are non-creditworthy.
- Logistic Regression Model predicted 13 persons as non-creditworthy and actually are creditworthy. Also, it predicted 23 persons as creditworthy and actually are non-creditworthy.

You should have four sets of questions answered. (500 word limit)

Step 4: Writeup

Decide on the best model and score your new customers. For reviewing consistency, if Score_Creditworthy is greater than Score_NonCreditworthy, the person should be labeled as "Creditworthy"

Write a brief report on how you came up with your classification model and write down how many of the new customers would qualify for a loan. (250 word limit)

Answer these questions:

- Which model did you choose to use?

Model Comparison Report

Fit and error measures

Model	Accuracy	F1	AUC	Accuracy_Creditworthy	Accuracy_Non-Creditworthy
DTM	0.7467	0.8273	0.7054	0.8667	0.4667
FM	0.8000	0.8707	0.7361	0.9619	0.4222
BM	0.7867	0.8632	0.7524	0.9619	0.3778
LRM	0.7600	0.8364	0.7306	0.8762	0.4889

Model: model names in the current comparison.
Accuracy: overall accuracy, number of correct predictions of all classes divided by total sample number.
Accuracy_[class name]: accuracy of Class [class name] is defined as the number of cases that are **correctly** predicted to be Class [class name] divided by the total number of cases that actually belong to Class [class name], this measure is also known as *recall*.
AUC: area under the ROC curve, only available for two-class classification.
F1: F1 score, 2 * precision * recall / (precision + recall). The *precision* measure is the percentage of actual members of a class that were predicted to be in that class divided by the total number of cases predicted to be in that class. In the situations where there are three or more classes, average precision and average recall values across classes are used to calculate the F1 score.

Please justify your decision using **all** of the following techniques. Please only use these techniques to justify your decision:

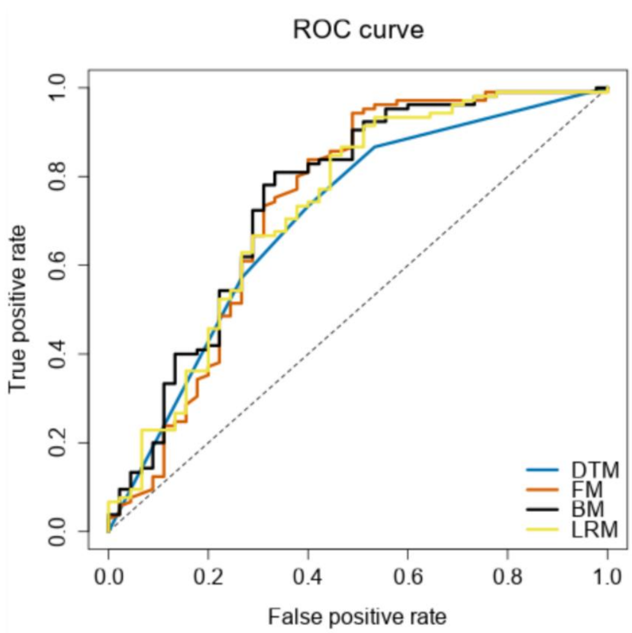
- Overall Accuracy against your Validation set

  From Model Comparison Report, the best model is the Forest Model as we see the highest number of accuracy which is 0.80 for the Forest Model.

- Accuracies within “Creditworthy” and “Non-Creditworthy” segments

  Forest Model and Boosted Tree Model have the highest number of Accuracy_Creditworthy which is 0.96, but for Accuracy_Non-Creditworthy, Boosted Model has the lowest value which is 0.37. The highest number of Accuracy_Non-Creditworthy is 0.48 for Logistic Regression Model

- ROC graph



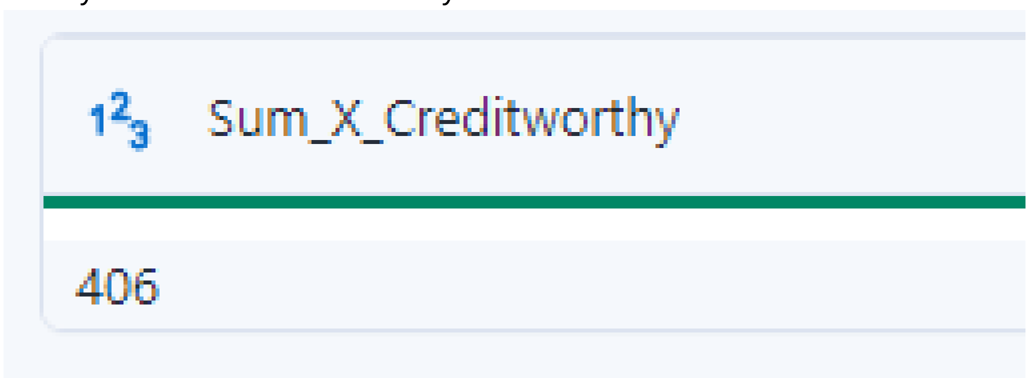
From ROC curve plot, the Decision Tree Model is the worst model due to it is the nearest to the diagonal line. The Forest Model is the farthest curve from the diagonal line, so it is the best model.

- ○ Bias in the Confusion Matrices

From the Confusion matrix of Models and which I explained before, I can say the Forest Model is the best model for predicting creditworthy comparing with remaining models.

Note: Remember that your boss only cares about prediction accuracy for Creditworthy and Non-Creditworthy segments.

- How many individuals are creditworthy?



Sum_X_Creditworthy
406

The Forest Model predicted 406 persons out of 500 persons are creditworthy

Before you Submit

Please check your answers against the requirements of the project dictated by the rubric here. Reviewers will use this rubric to grade your project.