

Project: Creditworthiness

Step 1: Business and Data Understanding

Key Decisions:

Answer these questions

- What decisions needs to be made?

The company suddenly has an influx of nearly 500 loan applications to process this week. The manager needs to come up with an efficient and accurate classification model that can systematically evaluate all these loan applications within one week.

- What data is needed to inform those decisions?

Data on all past applications.

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

Since the credit application result consists of two categories, i.e., Creditworthy or Non-Creditworthy, a binary model is used to make these decisions.

Step 2: Building the Training Set

*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”.

| FieldName | Duration-of-Credit-Month | Credit-Amount | Instalment-per-cent | Most-valuable-available-asset | Age-years | Type-of-apartment | No-of-dependents |
|-------------------------------|--------------------------|---------------|---------------------|-------------------------------|-----------|-------------------|------------------|
| Duration-of-Credit-Month | 1 | 0.57398 | 0.068106 | 0.299855 | -0.064197 | 0.152516 | -0.065269 |
| Credit-Amount | 0.57398 | 1 | -0.288852 | 0.325545 | 0.069316 | 0.170071 | 0.003986 |
| Instalment-per-cent | 0.068106 | -0.288852 | 1 | 0.081493 | 0.03927 | 0.074533 | -0.125894 |
| Most-valuable-available-asset | 0.299855 | 0.325545 | 0.081493 | 1 | 0.086233 | 0.373101 | 0.046454 |
| Age-years | -0.064197 | 0.069316 | 0.03927 | 0.086233 | 1 | 0.32935 | 0.117736 |
| Type-of-apartment | 0.152516 | 0.170071 | 0.074533 | 0.373101 | 0.32935 | 1 | 0.170738 |
| No-of-dependents | -0.065269 | 0.003986 | -0.125894 | 0.046454 | 0.117736 | 0.170738 | 1 |

Based on the correlation matrix shown above, no numerical data field has a high correlation with others.

- Are there any missing data for each of the data fields? Fields with a lot of missing data should be removed

By exploring the data using the Field Summary tool in Alteryx, 68.8% of field Duration In Current Address is missing. Besides, 2.4% of field Age Years is missing.

- 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.

Using the same tool mentioned in the previous question, the result shows that fields including Occupation and Concurrent Credits look very uniform. Fields such as Guarantors, Foreign Worker, No-of-dependents show “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.



As I mentioned before, there are too many missing values in the field Duration In Current Address to impute, so it is better to be removed. Fields with uniform or “low variability” as mentioned before are removed. Field Age Years is imputed with median strategy since there is only 2.4% missing values.

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

*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.

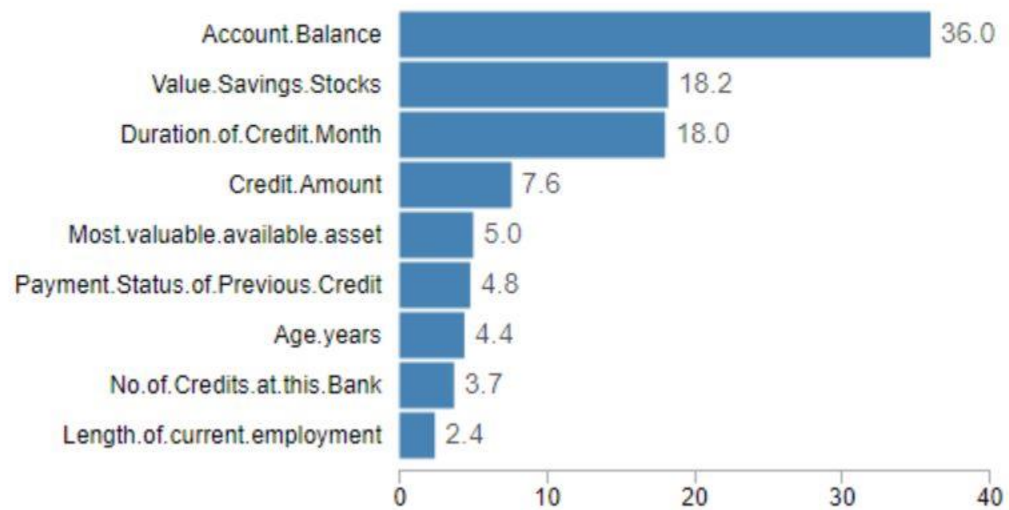
Coefficients:

| | Estimate | Std. Error | z value | Pr(> z) |
|------------------------------------------------|------------|------------|---------|--------------|
| (Intercept) | -3.0136120 | 1.013e+00 | -2.9760 | 0.00292 ** |
| Account.BalanceSome Balance | -1.5433699 | 3.232e-01 | -4.7752 | 1.79e-06 *** |
| Duration.of.Credit.Month | 0.0064973 | 1.371e-02 | 0.4738 | 0.63565 |
| Payment.Status.of.Previous.CreditPaid Up | 0.4054309 | 3.841e-01 | 1.0554 | 0.29124 |
| Payment.Status.of.Previous.CreditSome Problems | 1.2607175 | 5.335e-01 | 2.3632 | 0.01812 * |
| PurposeNew car | -1.7541034 | 6.276e-01 | -2.7951 | 0.00519 *** |
| PurposeOther | -0.3191177 | 8.342e-01 | -0.3825 | 0.70206 |
| PurposeUsed car | -0.7839554 | 4.124e-01 | -1.9008 | 0.05733 . |
| Credit.Amount | 0.0001764 | 6.838e-05 | 2.5798 | 0.00989 *** |
| Value.Savings.StocksNone | 0.6074082 | 5.100e-01 | 1.1911 | 0.23361 |
| Value.Savings.Stocks£100-£1000 | 0.1694433 | 5.649e-01 | 0.3000 | 0.7642 |
| Length.of.current.employment4-7 yrs | 0.5224158 | 4.930e-01 | 1.0596 | 0.28934 |
| Length.of.current.employment< 1yr | 0.7779492 | 3.956e-01 | 1.9664 | 0.04925 ** |
| Instalment.per.cent | 0.3109833 | 1.399e-01 | 2.2232 | 0.0262 ** |
| Most.valuable.available.asset | 0.3258706 | 1.556e-01 | 2.0945 | 0.03621 ** |
| Age.years | -0.0141206 | 1.535e-02 | -0.9202 | 0.35747 |
| Type.of.apartment | -0.2603038 | 2.956e-01 | -0.8805 | 0.3786 |
| No.of.Credits.at.this.BankMore than 1 | 0.3619545 | 3.815e-01 | 0.9487 | 0.34275 |

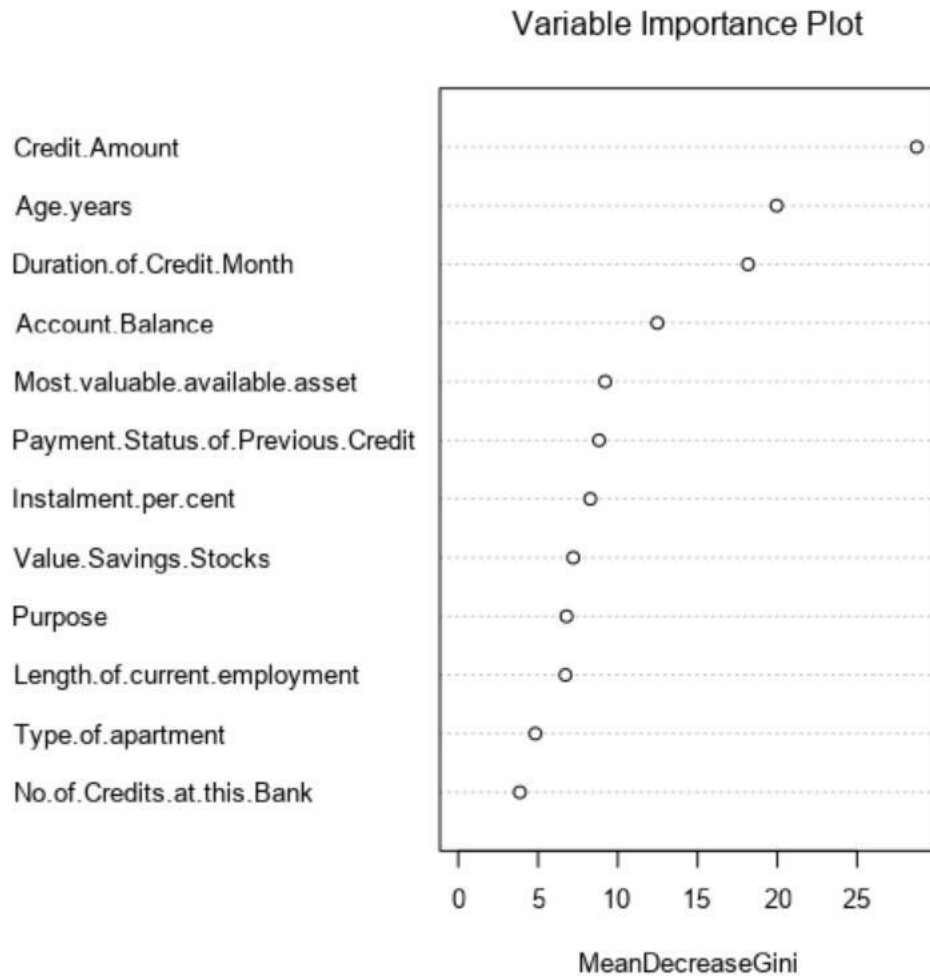
Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Based on the result of the Logistic Regression model shown above, predictors including subcategory Some Balance of Account Balance, subcategory Some Problems of Payment Status of Previous Credit, subcategory New Car of Purpose, Credit Amount, subcategory < 1yr of Length of Current Employment, Instalment per cent and Most Valuable Available Asset are statistically significant at the level of 0.05.

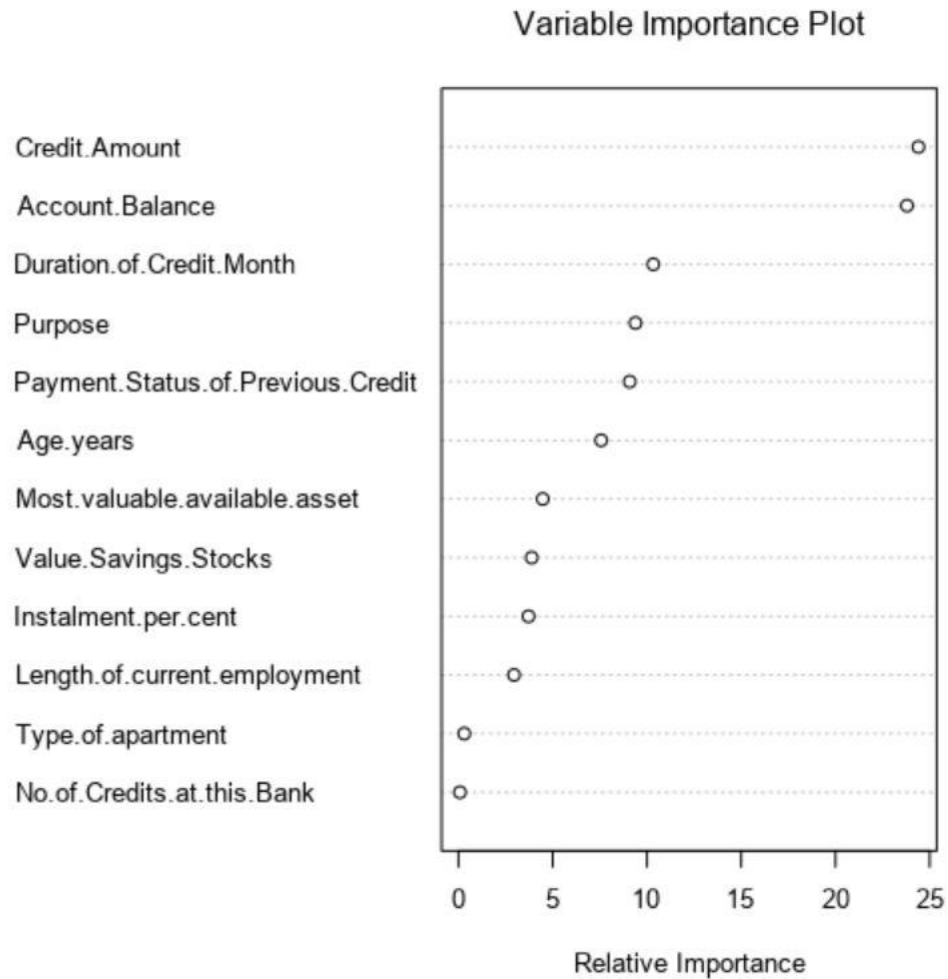
Variable Importance



For the Decision Tree model, based on the variable importance shown above, predictors including Account Balance, Value Savings Stocks and Duration of Credit Month are the three most important ones.



For the Random Forest model, the variable importance plot shows that predictors such as Credit Amount, Age Years and duration of Credit Month are the three most important ones.



For the Boosted model, the variable importance plot shows that predictors such as Credit Amount, Account Balance and Duration of Credit Month are the three most important ones.

- 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?

| Fit and error measures | | | | | |
|------------------------|----------|--------|--------|-----------------------|---------------------------|
| Model | Accuracy | F1 | AUC | Accuracy_Creditworthy | Accuracy_Non-Creditworthy |
| logistic | 0.7800 | 0.8520 | 0.7314 | 0.8051 | 0.6875 |
| dt | 0.7467 | 0.8273 | 0.7054 | 0.7913 | 0.6000 |
| rf | 0.7933 | 0.8661 | 0.7368 | 0.7846 | 0.8500 |
| bt | 0.7867 | 0.8632 | 0.7524 | 0.7829 | 0.8095 |

The overall percent accuracy is around 78% for all the models but Decision Tree model (around 75%).

| Confusion matrix of bt | | |
|----------------------------|---------------------|-------------------------|
| | Actual_Creditworthy | Actual_Non-Creditworthy |
| Predicted_Creditworthy | 101 | 28 |
| Predicted_Non-Creditworthy | 4 | 17 |

| Confusion matrix of dt | | |
|----------------------------|---------------------|-------------------------|
| | Actual_Creditworthy | Actual_Non-Creditworthy |
| Predicted_Creditworthy | 91 | 24 |
| Predicted_Non-Creditworthy | 14 | 21 |

| Confusion matrix of logistic | | |
|------------------------------|---------------------|-------------------------|
| | Actual_Creditworthy | Actual_Non-Creditworthy |
| Predicted_Creditworthy | 95 | 23 |
| Predicted_Non-Creditworthy | 10 | 22 |

| Confusion matrix of rf | | |
|----------------------------|---------------------|-------------------------|
| | Actual_Creditworthy | Actual_Non-Creditworthy |
| Predicted_Creditworthy | 102 | 28 |
| Predicted_Non-Creditworthy | 3 | 17 |

Based on the confusion matrices of all the models shown above, it is more difficult to predict Non-Creditworthy than Creditworthy since the false positive rate is higher than the false negative rate for each model.

Step 4: Writeup

Decide on the best model and score your new customers. For reviewing consistency, if $\text{Score_Creditworthy}$ is greater than $\text{Score_NonCreditworthy}$, 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? 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
 - Accuracies within "Creditworthy" and "Non-Creditworthy" segments
 - ROC graph
 - Bias in the Confusion Matrices

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

Since the manager cares about prediction accuracy for both Creditworthy and Non-Creditworthy segments and the model was trained in a dataset which there are more Creditworthy instances than Non-Creditworthy ones, the F1 measure should be the appropriate measure in this context. Among all these models, the Random Forest model is the best since it has the highest F1 measure against the Validation dataset. In addition, the Random Forest model has the highest accuracy rate and AUC score, too.

- How many individuals are creditworthy?

There are 408 individuals are classified as creditworthy based on the Random Forest model.

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Alteryx workflow:

