# GERMAN CREDIT CARD

Analysis & Recommendations

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# BUSINESS PROBLEM

- **Problem Statement**: Given a loan application, a German Bank needs to make the right decision whether to approve or disapprove a potential client.
- **Solution:** Create a machine learning model to predict the right decision of a loan application

# DATA PREPARATION

# SUMMARY OF GIVEN DATA

- 1,000 instances with 21 attributes
- Class attribute (Credibility) describes instances as good or bad
  - 700 good credit cases
  - 300 bad credit cases
- Attribute Classification – 6 Numeric, 10 Nominal, 5 Ordinal
- E.g. of attributes: Type of apartment, Credit Amount, Value savings/stocks etc.

# NUMERICAL DATA SUMMARY

- **Duration of Credit**

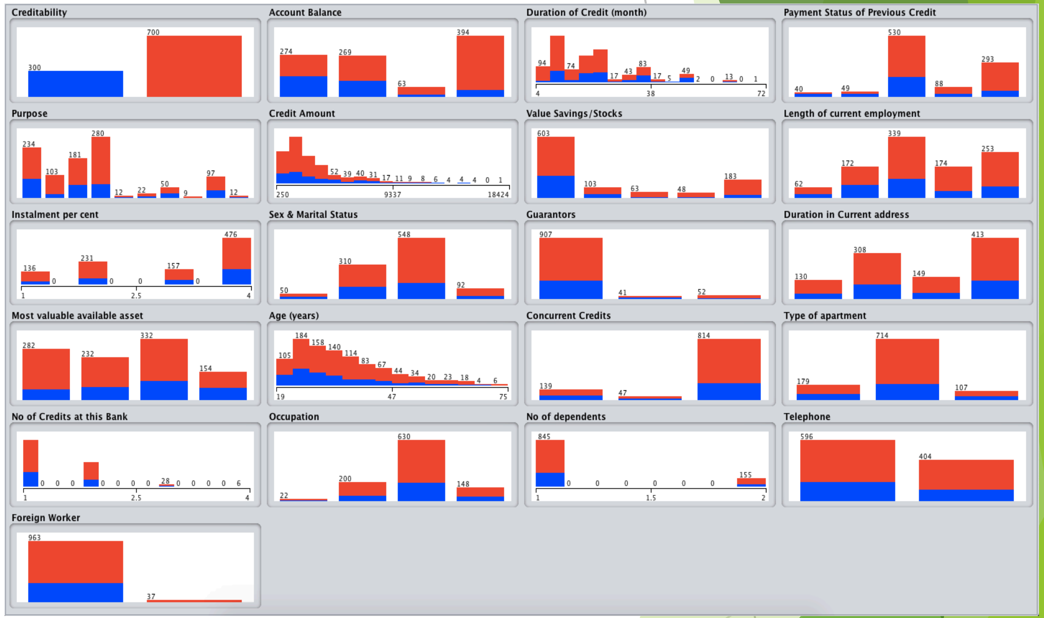
  Average approximately 21 months

- **Credit Amount**
  - Has a right skewed distribution, and there are more people with smaller amounts of credit comparatively. Maximum amount for the loan is $18,424
- **Instalment per cent**
  - Significant number of people have an instalment rate of 3-4%. The distribution is slightly skewed to the left.
- **Age**
  - Young people are more likely to apply for a loan (early 30s). The distribution is right skewed in this case as well.
- **No. of Credits at this Bank**
  - More than 50% of the data has only 1 credit at this bank i.e. median value was 1
- **No. of Dependents:**
  - 75% or more people have only 1 dependent in their credit application

| Attribute | Maximum | Minimum | Mean | Median | Std. Deviation |
|---|---|---|---|---|---|
| Duration of credit (month) | 72 | 4 | 20.903 | 18 | 12.059 |
| Credit Amount | 18424 | 250 | 3271.25 | 2320 | 2822.752 |
| Installment per cent | 4 | 1 | 2.973 | 3 | 1.119 |
| Age (years) | 75 | 19 | 35.542 | 33 | 11.353 |
| No. of Credits at this Bank | 4 | 1 | 1.407 | 1 | 0.578 |
| No. of dependents | 2 | 1 | 1.155 | 1 | 0.362 |

# DISTRIBUTION OF ATTRIBUTES

- **Outlier & Missing Value**
  - Outliers were not removed. Due to a small number of observations, we believe that all data points are important to the bank.
- **Comparison of Numerical Attributes with class attribute**
  - **Age:** People who are below the age of 40 tend to apply for a loan. Early part of the histogram has higher a frequency
  - **Credit Amount:** People tend to seek a credit amount less than 8,000
  - **No of Credits at this Bank:** Population with just one existing loan tend to apply for a new loan
  - **Occupation:** Skilled employees constituted most of the population who applied for a loan
  - **Sex & Marital Status:** Males who are single, constituted most of the population who had applied for loan.



# FEATURE SELECTION

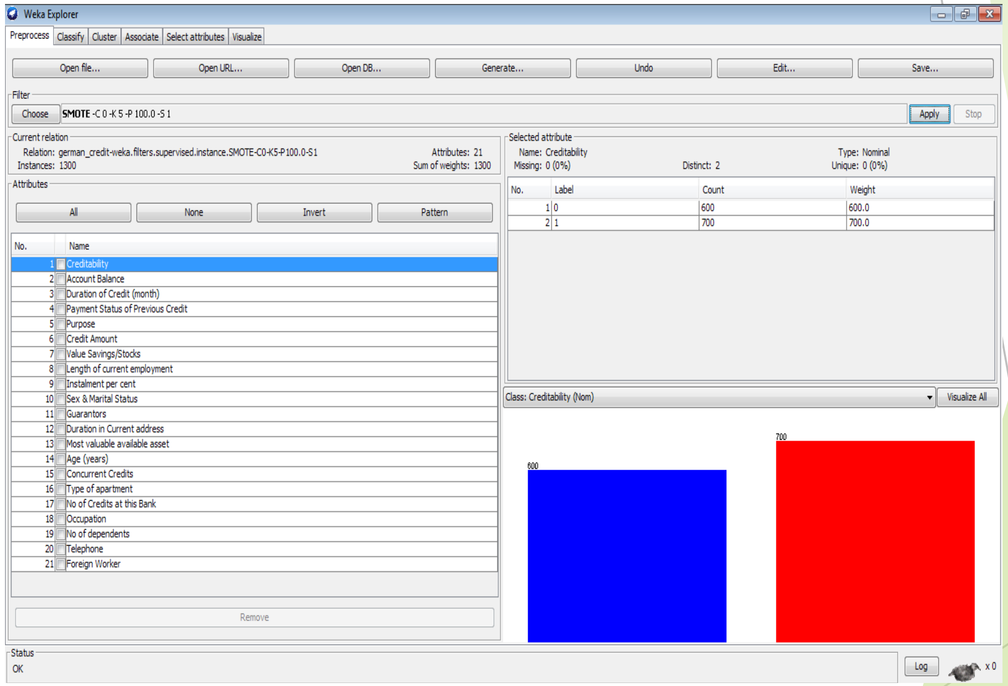
- Below are the feature selection methods that were used to identify attributes which contribute the most
  - Correlation
  - Information Gain
  - Learner Based – J48
  - Chi-Square
  - Symmetrical Uncertainty
- Attributes Identified
  1. Account Balance
  2. Value Savings/Stocks
  3. Duration of Credit (Month)
  4. Purpose
  5. Payment Status of Previous Credit

| Attribute | Correlation | Information Gain | Learner based - J48 | Chi-Square | Symmetrical Uncertainty |
|---|---|---|---|---|---|
| Account Balance | **0.23276** | **0.094739** | **1** | **123.7209** | **0.070613** |
| Duration of Credit (month) | **0.21493** | **0.0329** | **2** | **46.8311** | **0.030272** |
| Value Savings/Stocks | **0.13162** | **0.028115** | **4** | **36.0989** | **0.021887** |
| Payment Status of Previous Credit | **0.08988** | **0.043618** | **3** | **61.6914** | **0.033641** |
| Credit Amount | **0.15474** | **0.018333** | | **26.3992** | **0.021448** |
| Type of apartment | 0.12283 | 0.013077 | | 18.674 | 0.012963 |
| Purpose | 0.07494 | 0.024894 | | **33.3564** | **0.014033** |
| Length of current employment | 0.0527 | 0.013102 | | 18.3683 | 0.00863 |
| Instalment per cent | 0.0724 | 0 | | 0 | 0 |
| Sex & Marital Status | 0.07192 | 0.006811 | | 9.6052 | 0.005644 |
| Most valuable available asset | 0.05838 | 0.016985 | | 23.7196 | 0.012008 |
| Age (years) | 0.09127 | 0.011278 | | 16.3681 | 0.014251 |
| Concurrent Credits | 0.108 | 0.008875 | | 12.8392 | 0.010284 |
| Occupation | 0.01904 | 0.001337 | **5** | 1.8852 | 0.001166 |
| Foreign Worker | 0.08208 | 0.005823 | **6** | 6.737 | 0.010495 |
| No of dependents | 0.00301 | 0 | | 0 | 0 |
| No of credit at this Bank | 0.04573 | 0 | | 0 | 0 |
| Guarantors | 0.00612 | 0.00479 | | 6.6454 | 0.006758 |
| Duration in current Address | 0.01096 | 0.000543 | | 0.7493 | 0.000398 |
| Telephone | 0.03647 | 0.000964 | | 1.3298 | 0.001039 |

# PREDICTIVE MODELING

# CLASSIFICATION & SMOTE

- **Classification** is a two-step process
  1. Learning step
     - Model is developed based on given training data
  2. Prediction step
     - Model is used to predict the response for a given data
- **Three** classification algorithms were used
  - Naïve Bayes
  - Decision Tree
  - Logistic Regression
- **SMOTE**
  - 300 additional records (synthetic data) were added to class 0 in order to balance the data set.
  - Increased the total number observations belonging to class 0 to 600 and total records to 1300



# NAÏVE BAYES

- Probability-based machine learning model
- The classifier is based on the Bayes theorem

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

- Fast & easy classifier
- Performs well in case of categorical variable compared to numerical variables

# NAÏVE BAYES TESTS & RESULTS

## Summary of Tests and Results

- Tests were performed using all 20 attributes and later selecting only the top 6 attributes. No significant improvement in accuracy was observed when the number of parameters were decreased
- Dataset was split using strategies such as 10-Fold and percentage split techniques (60-40). When using an unbalanced dataset, a 10-fold split strategy performed better
- When using a balance dataset (SMOTE). The Maximum **Accuracy** was achieved by using a 60-40% split.

**Balanced Data with 20 Attributes (with SMOTE)**

| Algorithm (Naive Bayes) | Cross Validation, K= 10, | Percentage Split, 60% | Percentage Split, 90% |
|---|---|---|---|
| Correctly Classified instances (%) | 80% | **80.9%** | 83.8% |
| Incorrectly Classified instances (%) | 20% | 19.8% | 16.1% |
| F-Score | 0.800 | 0.803 | 0.839 |
| Precision rate | 0.800 | 0.804 | 0.840 |
| Recall rate | 0.800 | 0.802 | 0.838 |

**Confusion matrix**

| | Classified | |
|---|---|---|
| Test Data | Good application | Bad Application |
| Good application | 47 | 9 |
| Bad application | 12 | 62 |
| | Accuracy = (47+62)/130 = 83.8% | |

# DECISION TREE

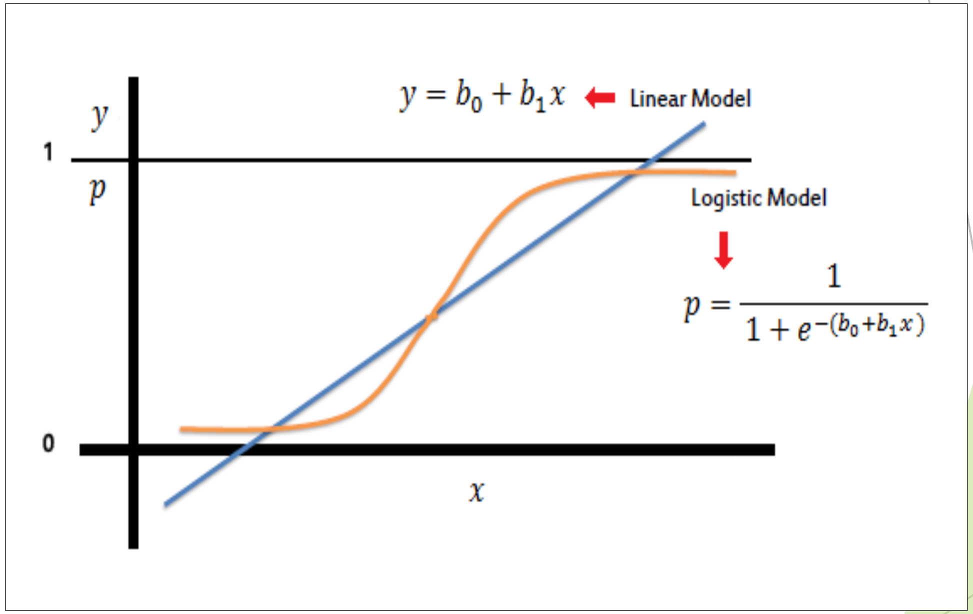
- Supervised learning algorithm
- Used for solving Regression and Classification problems
- Data is split into Nodes and Leaves
- **J48** classifier was used in Weka for Decision Tree

# DECISION TREE TESTS SUMMARY

- Account Balance was the root node in all the test cases as it had the highest gain
- A total of 16 tests were performed and Pruning was set to True
- All 20 independent attributes used to construct a decision tree and two types of testing techniques were used
  - 10-fold test: accuracy of 72.8%
  - Percentage Split (ratio of 60:40): accuracy of 71.8%
- SMOTE improved the accuracy of the model
  - 78.4 % accuracy using J48 algorithm on a total of 520 test records
  - Bagging technique used to check if overfitting was caused
    - Highest accuracy of 79.4% with a combination of Bagging + SMOTE + Percentage Split Test
- Same tests conducted on 6 attributes
  - Highest accuracy of 78.4% achieved by combination of Bagging + SMOTE + Percentage Split Test
- Decreasing the number of attributes to 6 did not make any improvement in the classification of the model

# LOGISTIC REGRESSION

- Logistic Regression is a linear method
- Predictions are transformed using the logistic function in order to get a probability between 0 and 1.
- Threshold was set at 0.5, output greater than 0.5 will be classified as good credit individual



# LOGISTIC REGRESSION SUMMARY

- Accuracy varied between 70 and 75% in all the test cases
- Best strategy to split the dataset is 10-fold cross validation rather than a simple percentage split
  - All instances have a higher accuracy using the cross-validation training strategy. f-score confirms the same
- Best results in terms of accuracy was found to be 75.2% using all 20 attributes and a 10-fold strategy

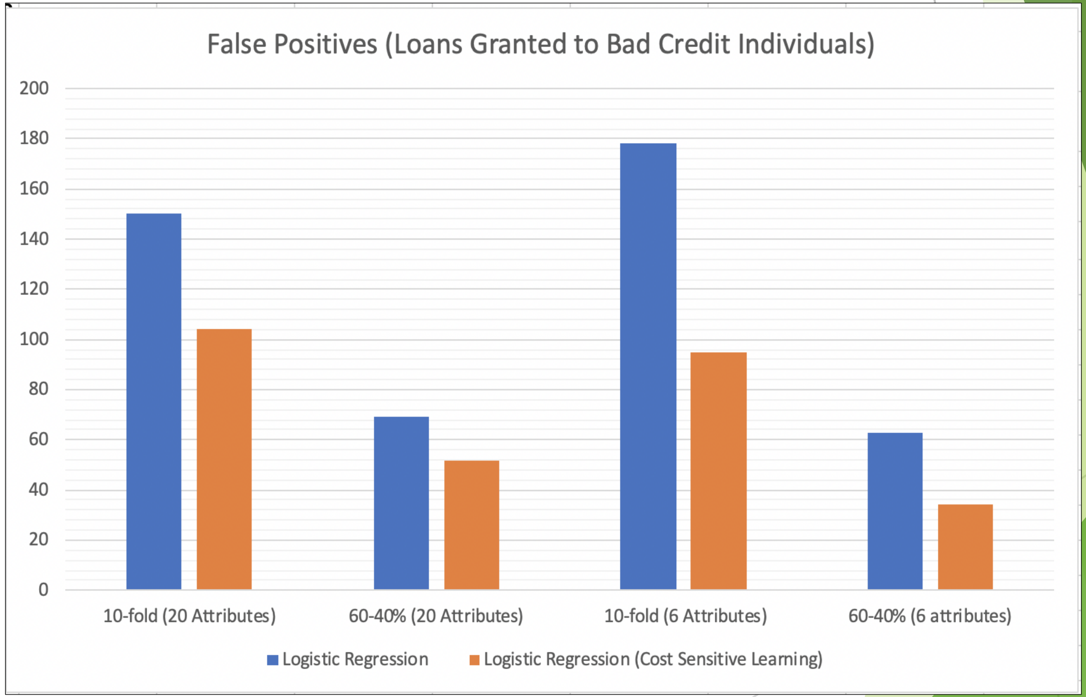
**Results of Logistic Regression on 20 Attributes**

| S. No | Parameters Used | No of Attributes | Cost Matrix | Test Data Method | Test Data Size | Accuracy (Correctly Classified Instances) | Weighted Precision | Weighted Recall | Weighted F Measure | Confusion Matrix |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Logistic regression | 20 | NA | 10-fold | 1000 | **75.20%** | 0.742 | 0.752 | **0.745** | a b <-- classified as 150 150 \| a = 0 98 602 \| b = 1 |
| 2 | Logistic Regression | 20 | NA | 60-40% | 400 | 73.50% | 0.725 | **0.735** | 0.725 | a b <-- classified as 66 69 \| a = 0 37 228 \| b = 1 |
| 3 | Logistic regression with cost sensitive learning | 20 | Cost Matrix 0 2 1 0 | 10-fold | 1000 | 72.40% | **0.745** | 0.724 | 0.731 | a b <-- classified as 196 104 \| a = 0 172 528 \| b = 1 |
| 4 | Logistic regression with cost sensitive learning | 20 | Cost Matrix 0 2 1 0 | 60-40% | 400 | 70.50% | 0.713 | 0.705 | 0.708 | a b <-- classified as 83 52 \| a = 0 66 199 \| b = 1 |

# LOGISTIC REGRESSION (COST SENSITIVE STRATEGY)

- **Cost sensitive model objective:**
  - To minimize the overall **error cost** and not optimize the correctness of classification
- metaclassifier CostSensitiveClassifier was chosen in WEKA and Cost matrix was updated.
- Cost sensitive strategy will not improve the **weighted** accuracy, precision and recall of the model but does improve the **false positive rate** of the model
- Out of all the bad credit individuals, the number of misclassifications is lower

**Logistic Regression Results Comparison**



# CLASSIFICATION ALGORITHMS COMPARISON

**Comparison of All Classification Algorithms**

| No | Algorithm | Testing Method | Number of Instances | Accuracy | Precision | Recall | F-Measure |
|---|---|---|---|---|---|---|---|
| 1 | Naive Bayes | 10-Fold Test | 1000 | **75.4** | 0.743 | 0.754 | 0.746 |
| 2 | Naive Bayes | 60-40 Split | 400 | 74.5 | 0.737 | 0.745 | 0.726 |
| 3 | Decision Tree | 10-Fold Test | 1000 | 72.8 | 0.712 | 0.728 | 0.716 |
| 4 | Decision Tree | 60-40 Split | 400 | 71.75 | 0.706 | 0.718 | 0.687 |
| 5 | Logistic Regression | 10-Fold Test | 1000 | 75.2 | 0.742 | 0.752 | 0.745 |
| 6 | Logistic Regression | 60-40 Split | 400 | 73.5 | 0.725 | 0.735 | 0.725 |

- The Highest accuracy of 75.4% was achieved with **Naïve Bayes** classification method on all 20 attributes and a 10-fold test
- 10-fold training/testing strategy yielded better results than a simple percentage split
- Introducing SMOTE improves the accuracy of the model but this may be due to overfitting

# POST-PREDICTIVE MODELING

# POST PREDICTIVE ANALYSIS

- To identify the characteristics of customer whose loans were approved as well as the characteristics of those who got disapproved

- Strategies used
  - Clustering Method – **K-Means**
  - Association Rules – **Apriori**

# K-MEANS

- K-Means algorithm was used for cluttering data and to find homogeneous subgroups within the data
- Partition the dataset into k pre-defined clusters. Points within a cluster are as similar as possible and inter-cluster distances are as far as possible
- It uses the sum of least squares technique. **Elbow method** was used to determine the number of clusters
- **Class to cluster** evaluation in K-Means was used to segregate the data, based on credibility
- **Three** different tests that we performed
  - Class to Cluster evaluation
  - Cluster population whose credit was approved (700)
  - Test on only those who were disapproved (300)

# K-MEANS RESULTS

**Cluster analysis of population whose credit was approved (700)**

- **Cluster 0** consists of middle-aged people who seek lower credit amount and seek loans for a short duration of time. Another characteristic of this population is that they have low valuable assets.
- **Cluster 1** consists of an older population who applied for a higher credit amount. people in this cluster also required a longer duration of credit. The credit purpose for these individuals leans towards a mean of 0. This means that these clients used the loan to buy a car.
- **Cluster 2** consisted of middle-aged clients who had applied for higher credit. The people in this cluster also applied for a longer duration of credit. An important trait of these customers consisted that they had 3 or more valuable assets.

**Cluster analysis of population who were disapproved (300)**

- Loan applicates in Cluster 0 were denied as they were old people who applied for very high credit amount. Bank regarded these individuals as being too risky.
- Both clusters consisted of young individuals who had relatively less experience but wanted long duration of credit. It is possible that their loan application was declined due to the high amount requested as well as lower job security.

**Class to Cluster evaluation**

- Account balance, payment status of previous credit, credit amount, instalment per cent, duration in current address and most valuable available asset are attributes which differentiates good and bad debtors.
- Accuracy of this experiment was low at 55%.

**Good Credit Clusters**

| Attribute | Full Data | Cluster# 0 | 1 | 2 |
|---|---|---|---|---|
| | (700.0) | (184.0) | (223.0) | (293.0) |
| Account Balance | 4 | 4 | 4 | 4 |
| Duration of Credit (month) | 19.2071 | 16.5761 | 19.157 | 20.8976 |
| Payment Status of Previous Credit | 2 | 2 | 4 | 2 |
| Purpose | 3 | 3 | 0 | 3 |
| Credit Amount | 2985.4429 | 2460.1196 | 3146.5695 | 3192.7065 |
| Value Savings/Stocks | 1 | 1 | 1 | 1 |
| Length of current employment | 3 | 2 | 5 | 3 |
| Instalment per cent | 2.92 | 2.5978 | 3.0493 | 3.0239 |
| Sex & Marital Status | 3 | 2 | 3 | 3 |
| Guarantors | 1 | 1 | 1 | 1 |
| Duration in Current address | 4 | 4 | 4 | 2 |
| Most valuable available asset | 3 | 1 | 2 | 3 |
| Age (years) | 36.22 | 34.1576 | 42.148 | 33.0034 |
| Concurrent Credits | 3 | 3 | 3 | 3 |
| Type of apartment | 2 | 2 | 2 | 2 |
| No of Credits at this Bank | 1.4243 | 1.2228 | 1.722 | 1.3242 |
| Occupation | 3 | 3 | 3 | 3 |
| No of dependents | 1.1557 | 1.0435 | 1.3004 | 1.116 |
| Telephone | 1 | 1 | 1 | 1 |
| Foreign Worker | 1 | 1 | 1 | 1 |

**Bad Credit Clusters**

| Attribute | Full Data | 0 | 1 |
|---|---|---|---|
| | (300.0) | (131.0) | (169.0) |
| Account Balance | 1 | 1 | 1 |
| Duration of Credit (month) | 24.86 | 26.542 | 23.5562 |
| Payment Status of Previous Credit | 2 | 2 | 2 |
| Purpose | 0 | 0 | 3 |
| Credit Amount | 3938.1267 | 4576.1603 | 3443.5562 |
| Value Savings/Stocks | 1 | 1 | 1 |
| Length of current employment | 3 | 5 | 3 |
| Instalment per cent | 3.0967 | 3.1832 | 3.0296 |
| Sex & Marital Status | 3 | 3 | 2 |
| Guarantors | 1 | 1 | 1 |
| Duration in Current address | 4 | 4 | 2 |
| Most valuable available asset | 3 | 4 | 3 |
| Age (years) | 33.96 | 40.1756 | 29.142 |
| Concurrent Credits | 3 | 3 | 3 |
| Type of apartment | 2 | 2 | 2 |
| No of Credits at this Bank | 1.3667 | 1.4427 | 1.3077 |
| Occupation | 3 | 3 | 3 |
| No of dependents | 1.1533 | 1.2901 | 1.0473 |
| Telephone | 1 | 1 | 1 |
| Foreign Worker | 1 | 1 | 1 |

# APRIORI

- To determine the association between attributes
- Association Algorithm applicable only to nominal, binary and unary data
- Numerical attributes in the data set were converted to Nominal using Discretize and NumericToNominal features in Weka
- Key Parameters
  - **Support**
    - Measures the popularity of an attribute in the dataset
  - **Confidence**
    - Measures the probability of attribute X being chosen, given attribute Y
- Association rules were established by performing tests on customers belonging to the good credit class

# ASSOCIATION RULES USING APRIORI

**Interpretation based on best rules found:**

- Debtors seek smaller credit amount
- Good debtors have lower savings
- Good debtors paid back their old loans
- Loan seeking population mostly constituted of foreign works
- Most of the loan applications which were approved did not require a guarantor
- Debtor who were foreign workers required no guarantors in 611 cases
- In most cases, debtor has only 1 dependent
- Debtor owns his/her apartment in 528 instances
- Debtors consisted of skilled employees

```
Best rules found:

 1. Foreign Worker=1 667 ==> Creditability=1 667    conf:(1)
 2. Guarantors=1 635 ==> Creditability=1 635    conf:(1)
 3. Guarantors=1 Foreign Worker=1 611 ==> Creditability=1 611    conf:(1)
 4. No of dependents=1 591 ==> Creditability=1 591    conf:(1)
 5. Concurrent Credits=3 590 ==> Creditability=1 590    conf:(1)
 6. No of dependents=1 Foreign Worker=1 569 ==> Creditability=1 569    conf:(1)
 7. Concurrent Credits=3 Foreign Worker=1 561 ==> Creditability=1 561    conf:(1)
 8. Guarantors=1 No of dependents=1 539 ==> Creditability=1 539    conf:(1)
 9. Guarantors=1 Concurrent Credits=3 538 ==> Creditability=1 538    conf:(1)
10. Type of apartment=2 528 ==> Creditability=1 528    conf:(1)
11. Guarantors=1 No of dependents=1 Foreign Worker=1 524 ==> Creditability=1 524    conf:(1)
12. Guarantors=1 Concurrent Credits=3 Foreign Worker=1 517 ==> Creditability=1 517    conf:(1)
13. Type of apartment=2 Foreign Worker=1 504 ==> Creditability=1 504    conf:(1)
14. Concurrent Credits=3 No of dependents=1 503 ==> Creditability=1 503    conf:(1)
15. Concurrent Credits=3 No of dependents=1 Foreign Worker=1 485 ==> Creditability=1 485    conf:(1)
16. Guarantors=1 Type of apartment=2 476 ==> Creditability=1 476    conf:(1)
17. Guarantors=1 Concurrent Credits=3 No of dependents=1 461 ==> Creditability=1 461    conf:(1)
18. Guarantors=1 Type of apartment=2 Foreign Worker=1 458 ==> Creditability=1 458    conf:(1)
19. Guarantors=1 Concurrent Credits=3 No of dependents=1 Foreign Worker=1 449 ==> Creditability=1 449    conf:(1)
20. Type of apartment=2 No of dependents=1 446 ==> Creditability=1 446    conf:(1)
21. Occupation=3 444 ==> Creditability=1 444    conf:(1)
22. Concurrent Credits=3 Type of apartment=2 444 ==> Creditability=1 444    conf:(1)
23. No of Credits at this Bank=1 433 ==> Creditability=1 433    conf:(1)
24. Type of apartment=2 No of dependents=1 Foreign Worker=1 429 ==> Creditability=1 429    conf:(1)
25. Occupation=3 Foreign Worker=1 428 ==> Creditability=1 428    conf:(1)
```

```
Best rules found:

 1. Credit Amount='(-inf-3279]' 483 ==> Creditability=1 483    conf:(1)
 2. Value Savings/Stocks=1 386 ==> Creditability=1 386    conf:(1)
 3. Payment Status of Previous Credit=2 361 ==> Creditability=1 361    conf:(1)
 4. Account Balance=4 348 ==> Creditability=1 348    conf:(1)
 5. Duration of Credit (month)='(-inf-15.333333]' 342 ==> Creditability=1 342    conf:(1)
 6. Duration of Credit (month)='(-inf-15.333333]' Credit Amount='(-inf-3279]' 303 ==> Creditability=1 303
```

# CONCLUSION BASED ON APRIORI

- Based on the association rules derived using Apriori Algorithm, we recommend to the bank that good debtors are people:
  - Who do not require guarantors
  - Have no additional loans
  - Have less dependents
  - Own their household
  - Have low savings and are interested to borrow
  - Pay off loans in a timely manner
- Bank managers should not approve loans of people whose checking account balance is < 0 DM (Deutsche Mark) and average balance in savings and stocks is <100 DM. These customers are risky and may not be capable of fulfilling their credit obligations.

# RECOMMENDATIONS

- Attributes such as age, most valuable available assets, purpose, credit history, and employment skill levels are important factors to determine the credibility of a potential client

- Creditable borrowers don’t need guarantors, have no other loans/credits with no existing instalment plans, have fewer dependents, own their own apartments, have low savings, and pay off loans on time. Low risk loans also consist of those that are lower in amount and duration. Based on these recommendations, prospective borrowers not profiled as creditable should have markers that deviate from the profile above.

- Some of the “top 6 features” like value savings/stocks yielded common results between good credit and bad credit individuals. As a result, additional features beyond ‘the top 6’ are highly recommended to be used by the bank in order to make the right decisions.

THANK YOU