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Step by Step Guide on How to build a simple Credit Scorecard

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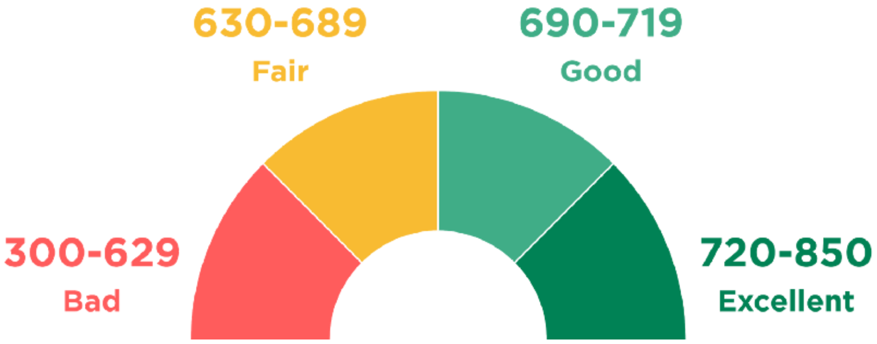

Source: NerdWallet

## Background

In the rise of fintech start-ups, there have been many new consumer credit lenders set up in the last 5 years competing with the traditional banks. They often target niche segments that banks deem too small or had to trim back lending on post losses incurred during the financial crisis.

One of the main competitive advantages for these new online-only consumer lenders is the tech element, without the drag of legacy I.T. systems present for every large bank, they have set up systems that are much faster, paperless, more user-friendly with mobile interface and utilising new sources of data in addition to the traditional financial data in the underwriting process.

For example, business loan lender iwoca uses info from linked company accounts, VAT returns and even sales transactions on ebay or amazon to determine new loans. Consumer loan lender lendable prides themselves on giving out personalised loan quotes within minutes rather than days or weeks that it can take at a traditional bank.

With the promise of fast and automatic decisions, they reply on having automatic and fast credit risk models to assess risk. In this post and in later posts, I propose to introduce the most common machine learning models used in the consumer finance credit risk space.

## What is a Credit Scorecard

SALARY LOANS- $5. —TO— $50
ONE WAY
THE LIBERTY FINANCE CO.
Loans MADE ON Autos Furnitures OR Anything of Value
LOANS ON YOUR SALARY $5⁰⁰ to $50⁰⁰
Low Cost Prompt Service!
SALARY CHATTEL LOANS
COTTON EXCHANGE BUILDING

Photo by The New York Public Library on Unsplash

Most of us are familiar with the concept of a **credit score**, this is a numeric value that represents the creditworthiness of an individual. All credit lending institutions like banks have complex credit models that use the information contained in the application like salary, credit commitments and past loan performances to determine a credit score of an application or an existing customer. The model outputs a score that represents how likely the lender will be repaid on time if they give a person a loan or a credit card.

A credit scorecard is one of such credit models, it is one of the most common credit models due to the fact it is relatively easy to interpret for customers and that it has been around for the last few decades, hence the development process is standard and widely understood.

However, it is worth to note that the range of score may be different from institution to institution, and the cut-off point for reject applications with lower score would vary from lender to lender and may even differ in the same lender but for different products.

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## Building a Credit Scorecard

The target variable usually takes a binary form, depending on the data, it can be 0 for performing customers and 1 to indicate defaulted customers or customers more than 90 days late on their payment. In the rest of this article, we will refer "Bad Customers" as the ones in some sort of default, and "Good Customer" for the others.

### STEP 1: Data Exploration and Cleaning

An essential step in all model fitting, but since it's not specific to building a credit scorecard model, so we will skip this section. Don't forget to split the data set into train and test dataset also.

### STEP 2: Data Transformation — Weight of Evidence Method

We then need to transform all the independent variables (like age, income etc.) using the weight of evidence (WoE) method. Based on the proportion of good applicants to bad applicants at each group level, this method measures the "strength" of grouping for differentiating good and bad risk, and attempts to find a monotonic relationship between the independent variables and the target variable.

**Transformation steps for a continuous variable:**

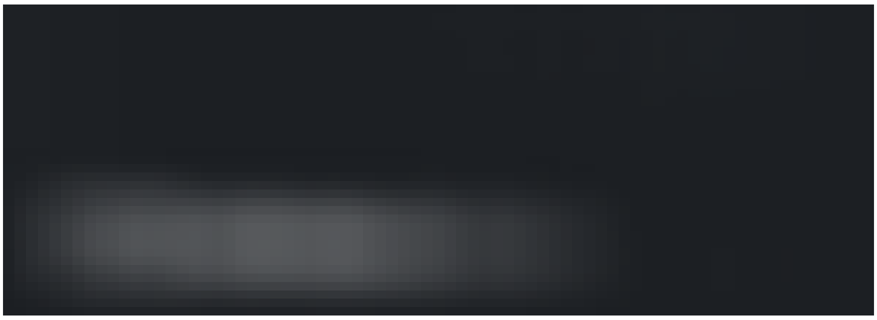
1. Split the data into bins, usually around 10, max of 20
2. Calculate the % of Good events and % Bad events
3. Calculate the WOE by taking the natural log

4. Replace the raw data with the calculated WOE values

*If the independent variable is categorical, then skip 1 above, and follow the rest of the steps.*

***An illustrated example in Python:***

After putting your data into bins, and grouping counts of bad and good for each bin so that your data may look something similar to the squared box below. WoE can be calculated using the code below for each bin group. Negative values indicate that a particular grouping contains a higher proportion of bad applicants than good applicants.



At the end of the transformation, if you had 20 independent variables to start with, you will now have 20 WOE_variablename columns to work with for the next step.

> ***Benefits of Using WoE transformation:***

- it helps to build a strict linear relationship with log-odds used in logistic regression
- it can handle missing values as these can be binned together
- outliers or extreme values can be handled as these are also binned, and the value that feeds into the model fitting is the WoE transformed value not the raw extreme value
- it also handles categorical value so no need for dummy variables

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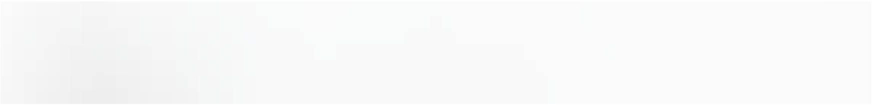
## STEP 3: Feature Selection using Information Value

Information Value (IV) comes from information theory, it measures the predictive power of independent variables which is useful in feature selection. Its good practice to perform feature selection to determine if it's necessary to include all the features in the model, most times we will want to eliminate weak features as a simpler model is usually preferred.

> *According to Siddiqi (2006), by convention, the values of the IV statistic in credit scoring can be interpreted as follows*

***An illustrated example in Python:***



Continuing with the illustrated example from before, here we calculate the IV of 'age' to be around 0.15, which implies age has "medium predictive power" and hence we will keep for model fitting. Variables with less than 0.02 IV score should be dropped.

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## STEP 4: Model Fitting & Interpreting Results

Now we fit a logistic regression model using our newly transformed WoE of the training dataset.

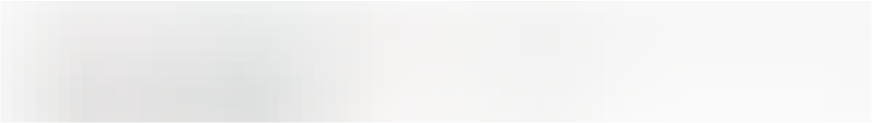
When scaling the model into a scorecard, we will need both the Logistic Regression coefficients from model fitting as well as the transformed WoE values. We will also need to convert the score from the model from the log-odds unit to a points system.

For each independent variable Xi, its corresponding score is:

$$Score\_i = (\beta i \times WoE\_i + \alpha/n) \times Factor + Offset/n$$

Where:
$\beta i$—logistic regression coefficient for the variable Xi
$\alpha$—logistic regression intercept
WoE—Weight of Evidence value for variable Xi
n—number of independent variable Xi in the model
Factor, Offset—known as scaling parameter, where

- Factor = pdo/ln(2)
- Offset = Target Score—(Factor × ln(Target Odds))



For the example above, we choose to have a **target score of 600** to mean a **50 to 1 odds** of good customer to bad, and an **increase of 20 means a doubling** odds. Note the choice of scaling does not affect the predictive strength of the scorecard.

The final total score is the sum of all scores based on the input values of the independent variables. The lender would then assess incoming applications based on the modelled total score and the cutoff point (which is set based on other credit default modelling).

$$Total\ Score = \Sigma\ Score\_i$$

An example of scorecard implementation, source { Credit Scoring—Scorecard Development Process by Sandy Liu, link at end of of this post}

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## Sources

1. Weight of evidence and information value explained
2. Replacing variables by WoE in Logistic Regression
3. Credit Scoring—Scorecard Development Process
4. Credit Scoring with Machine Learning