Credit scoring
Case study in data analytics

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This article presents some of the key features of Deloitte's Data Analytics solutions in the financial services.

As a concrete showcase we outline the main methodological steps for creating one of the most common solutions in the industry: A credit scoring model.

We emphasise the various ways to assess model performance (goodness-of-fit and predictive power) and some typical refinements that help improve it further.

We illustrate how to extract transparent interpretations out of the model, a holy grail for the success of a model to the business.

Contents

The advent of data analytics

Data has the potential to transform business and drive the creation of business value. Data can be used for a range of simple tasks such as managing dashboards or visualising relationships. However, the real power of data lies in the use of analytical tools that allow the user to extract useful knowledge and quantify the factors that impact events. Some examples include: Customer sentiment analysis, customer churn, geo-spatial analysis of key operation centres, workforce planning, recruiting, or risk-sensing.

Analytical tools are not the discovery of the last decade. Statistical regressions and classification models have been around for the best part of the 20th century. It is, however, the explosive growth of data in our times combined with the advanced computational power that renders data analytics a key tool across all businesses and industries.

In the Financial Industry some examples of using data analytics to create business value include fraud detection, customer segmentation, employee or client retention.

In order for data analytics to reveal its potential to add value to business, a certain number of ingredients need to be in place. This is particularly true in recent times with the explosion of big data (big implying data volume, velocity and variety). Some of these ingredients are the listed below:

Distributed file systems

The analysis of data requires some IT infrastructure to support the work. For large amounts of data the market standards are platforms like Apache Hadoop which consists of a component that is responsible for storing the data Hadoop *Distributed File System* (HDFS) and a component responsible for the processing of the data *MapReduce*. Surrounding this solution there is an entire ecosystem of additional software packages such as Pig, Hive, Spark, etc.

Database management

An important aspect in the analysis of data is the management of the database. An entire ecosystem of database systems exist: such as relational, object-oriented, NoSQL-type, etc. Well known database management systems include SQL, Oracle, Sybase. These are based on the use of a primary key to locate entries. Other databases do not require fixed table schemas and are designed to scale horizontally. Apache Cassandra for example is designed with the aim to handle big data and have no single point of failure.

Advanced analytics

Advanced analytics refers to a variety of statistical methods that are used to compute likelihoods for an event occurring. Popular software to launch an analytic solution are R, Python, Java, SPSS, etc. The zoo of analytics methods is extremely rich. However, as data does not come out of some industrial package, human judgement is crucial in order to understand the performance and possible pitfalls and alternatives of a solution.

Case study

In this document we outline one important application of advanced analytics. We showcase a solution to a common business problem in banking, namely assessing the likelihood of a client's default. This is done through the development of a credit scoring model.

Credit scoring

A credit scoring model is a tool that is typically used in the decision-making process of accepting or rejecting a loan. A credit scoring model is the result of a statistical model which, based on information about the borrower (e.g. age, number of previous loans, etc.), allows one to distinguish between "good" and "bad" loans and give an estimate of the probability of default. The fact that this model can allocate a rating on the credit quality of a loan implies a certain number of possible applications:

Application area	Description
Health score:	The model provides a score that is related to the probability that the client misses a payment. This can be seen as the “health” of the client and allows the company to monitor its portfolio and adjust its risk.
New clients	The model can be used for new clients to assess what is their probability of respecting to their financial obligations. Subsequently the company can decide to grant or not the requested loan.
What drives default	The model can be used to understand what the driving factors behind default are. The bank can utilise this knowledge for its portfolio and risk assessment.

A credit scoring model is just one of the factors used in evaluating a credit application. Assessment by a credit expert remains the decisive factor in the evaluation of a loan.

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The history of developing credit-scoring models goes as far back as the history of borrowing and repaying. It reflects the desire to issue an appropriate rate of interest for undertaking the risk of giving away one’s own money.

With the advent of the modern statistics era in the 20th century appropriate techniques have been developed to assess the likelihood of someone’s default on the payment, *given* the resemblance of his/her characteristics to those who have already defaulted in the past. In this document we will focus on one of the most prominent methods to do credit scoring, the logistic regression. Despite being one of the earliest methods of the subject, it is also one of the most successful, owing to its transparency.

Although credit scoring methods are linked to the aforementioned applications in banking and finance, they can be applied to a large variety of other data analytics problems, such as:

- Which factors contribute to a consumer’s choice?
- Which factors generate the biggest impact to a consumer’s choice?
- What is the profit associated with a further boost in each of the impact factors?
- How likely is that a customer likes to adopt a new service?
- What is the likelihood that a customer will go to a competitor?

Such questions can all be answered within the same statistical framework. A logistic regression model can, for example, provide not only the structure of dependencies of the explanatory variables to the default but also the statistical significance of each variable.

Data quality

Before statistics can take over and provide answers to the above questions, there is an important step of preprocessing and checking the quality of the underlying data. This provides a first insight into the patterns inside the data, but also an insight on the trustworthiness of the data itself. The investigation in this phase includes the following aspects:

What is the proportion of defaults in the data?

In order for the model to be able to make accurate forecasts it needs to see enough examples of what constitutes a default. For this reason it is important that there is a sufficiently large number of defaults in the data. Typically in practice, data with less than 5% of defaults pose strong modelling challenges.

What is the frequency of values in each variable in the data?

This question provides valuable insight into the importance of each of the variables. The data can contain numerical variables (for example, age, salary, etc.) or categorical ones (education level, marital status, etc.). For some of the variables we may notice that they are dominated by one category, which will render the remaining categories hard to highlight in the model. Typical tools to investigate this question are scatterplots and pie charts.

What is the proportion of outliers in the data?

Outliers can play an important role in the model's forecasting behaviour. Although outliers represent events that occur with a small probability and a high impact, it is often the case that outliers are a result of system error. For example, a numerical variable that is assigned to the value 999, can represent a code for a missing value, instead of a true numerical variable. That aside, outliers can be easily detected by the use of boxplots.

How many missing values are there and what is the reason?

Values can be missing for various reasons, which range from missing due to nonresponse, due to drop out of the clients, or due to censoring of the answers, or simply missing at random. Missing values pose the following dilemma: On one hand they refer to incomplete instances of data and therefore treatment or imputation may not reflect the exact state of affairs. However, avoiding to handle missing values and simply ignoring them may lead to loss of valuable information. There exists a number of ways to impute missing values, such as the expectation-maximisation algorithm.

Quality assurance

There is a standard framework around QA which aims to provide a full view on the data quality in the following aspects: Inconsistency, Incompleteness, Accuracy, Precision, Missing / Unknown.

Model development

Default definition

Before the analysis begins it is important to clearly state out what defines a default. This definition lies at the heart of the model. Different choices will have an impact on what the model predicts. Some typical choices for this definition include the cases that the client misses three payments in a row, or, that the sum of missed payments exceeds a certain threshold.

Classification

The aim of the credit scoring model is to perform a classification: To distinguish the “good” applicants from the “bad” ones. In practice this means the statistical models is required to find the separating line distinguishing the two categories, in the space of the explanatory variables (age, salary, education, etc.). The difficulty in the doing so is (i) that the data is only a sample from the true population (e.g. the bank has records only from the last 10 years, or the data describes clients of that particular bank) and (ii) the data is noisy which means that some of significant explanatory variables may not have been recorded or that the default occurred by accident rather than due to the explanatory factors.

Reject inference

Apart from this, there is an additional difficulty in the development of a credit scorecard for which there is no solution: For clients that were declined in the past the bank cannot possibly know what would have happened if they would have been accepted. In other words, the data that the bank has refers only to customer that were initially accepted for a loan. This means, that the data is already biased towards a lower default-rate. This implies that the model is not truly representative for a through-the-door client. This problem is often termed “reject inference”.

Logistic regression

One of the most common, successful and transparent ways to do the required binary classification to “good” and “bad” is via a logistic function. This is a function that takes as input the client characteristics and outputs the probability of default.

$$p = \frac{\exp(\beta_0 + \beta_1 \cdot x_1 + \cdots + \beta_n \cdot x_n)}{1 + \exp(\beta_0 + \beta_1 \cdot x_1 + \cdots + \beta_n \cdot x_n)}$$

where in the above

- p is the probability of default
- x_i is the explanatory factor i
- β_i is the regression coefficient of the explanatory factor i
- n is the number of explanatory variables

For each of the existing data points it is known whether the client has gone into default or not (i.e. p=1 or p=0). The aim in the here is to find the coefficients $\beta_0, \dots, \beta_n$ such that the model’s probability of default equals to the observed probability of default. Typically, this is done through maximum likelihood.

The above logistic function which contains the client characteristics in a linear way, i.e. as $\beta_0 + \beta_1 \cdot x_1 + \cdots + \beta_n \cdot x_n$ is just one way to make a logistic model. In reality, the default probability will depend on the client characteristics in a more complicated way.

Training versus generalisation error

In general terms, the model will be tested in the following way: The data will be split into two parts. The first part will be used for extracting the correct coefficients by minimising the error between model output and observed output (this is the so-called "training error").The second part is used for testing the "generalisation" ability of the model, i.e. its ability to give the correct answer to a new case (this is the so-called "generalisation error").

Typically, as the complexity of the logistic function increases (from e.g. linear to higher-order powers and other interactions) the training error becomes smaller and smaller: This means that the model learns from the examples to distinguish between "good" and "bad". The generalisation error is, however, the true measure of model performance because it is testing its predictive power. This is also reduced as the complexity of the logistic function increases. However, there comes a point where the generalisation error stops decreasing (with more examples) with the model complexity and thereafter starts increasing. This is the point of overfitting. This means that the model has learned to distinguish so well the two categories inside the training data that it has also learned the noise itself. The model has adapted so perfectly to the existing data (with all of its inaccuracies) and any new data point will be hard to classify correctly.

Variable selection

The first phase in the model development requires a critical view and understanding on the variables and a selection of the most significant ones. Failure to do so correctly can hamper the model's efficiency. This is a phase where human judgement and business intuition is critical in the success of the model. At first instance, we seek ways to reduce the number of available variables, for example, one can trace categorical variables where the majority of data lies within one category. Other tools from exploratory data analysis, such as contingency tables, are useful. They could indicate how dominant a certain category is with respect to all others. At a second instance, one can regroup categories of variables. The motivation for this comes from the fact that there may exist too many categories to handle (e.g. postcodes across a country), or certain categories may be linked and not able to stand alone statistically. Finally variable significance can be assessed in a more qualitative way by using Pearson's chi-squared test, the Gini coefficient or the Information Value criterion.

Information Value

The Information Value criterion is based on the idea that we perform a univariate analysis: We setup a multitude of models where there is only one explanatory variable and the response variable (the default). Among those models, the ones that describes best the response variable can indicate the most significant explanatory variables.

Information Value is a measure of how significant is the discriminatory power of a variable. Its definition is

$$IV(x) = \sum_{i=1}^{N(x)} \left(\frac{g_i}{g} - \frac{b_i}{b}\right) \cdot log\left(\frac{\frac{g_i}{g}}{\frac{b_i}{b}}\right)$$

where,

- *N(x)* is the number of levels in the variable *x*
- g_i represents the number of goods (no default) in category *i* of variable x_i
- b_i represents the number of bads (default) in category *i* of variable x_i
- *g* represents the number of goods (no default) in the entire dataset
- *b* represents the number of bads (default) in the entire dataset

To understand the meaning of the above expression let us go one step further. From the above it follows that:

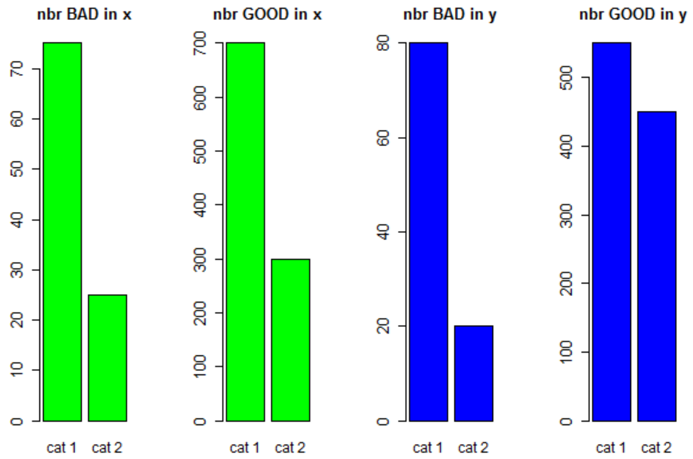
$$IV(x) = \sum_{i=1}^{N(x)} \left(\frac{g_i}{g}\right) \cdot log\left(\frac{\frac{g_i}{g}}{\frac{b_i}{b}}\right) - \sum_{i=1}^{N(x)} \left(\frac{b_i}{b}\right) \cdot log\left(\frac{\frac{g_i}{g}}{\frac{b_i}{b}}\right) \equiv D(g,b) + D(b,g)$$

It is easy to show that $D(\cdot,\cdot)$ is always non-negative using the so-called log-sum inequality:

$$D(g,b) \geq \left(\sum_{i=1}^{N(x)} \left(\frac{g_i}{g} \right) \right) \cdot log \left(\frac{\sum_i \frac{g_i}{g}}{\sum_i \frac{b_i}{b}} \right) = 0$$

Since *D* is non-negative, i.e. *D(x,y)>=0*, with *D(x,y)=0* if and only if *x=y*, the quantity *D* it can be used as a measure of "distance". Note that this is similar to the Kullback-Leibler distance.

To obtain some additional intuition concerning Information Value let us show the following four figures:



These represent two hypothetical categorical variables, named x and y. Each of these contains two categories, say category 1 and category 2. The ratio of "good" vs "bad" is the following:

VARIABLE x	GOOD	BAD	VARIABLE y	GOOD	BAD
Category 1 of x	700	75	**Category 1 of y**	550	80
Category 2 of x	300	25	**Category 2 of y**	450	20

From this example we notice that the proportion of goods versus bad in the variable x is almost the same, while in variable y there is a more pronounced difference. Thus we can anticipate the knowledge that a client belongs to category 1 of x will probably not give away his likelihood of future default, since category 2 of x has the same rate of good vs bad. The contrary with variable y. Computation of the Information Value of the two variables x and y gives: IV(x) = 0.0064 and IV(y) = 0.158. Since variable y has a higher Information Value we say that it has better classification power. Standard practise dictates that:

Classification power	Information Value
Poor	<0.15
Moderate	Between 0.15 and 0.4
Strong	>0.4

It is interesting to see how the same intuition can be obtained from a simple Bayesian argument. Computing the probability of a "good" within a category (say category 1) is:

$$P(G|cat\ 1) = \frac{P(G, cat\ 1)}{P(cat\ 1)} = \frac{P(cat\ 1|G)P(G)}{P(cat\ 1|G)P(G) + P(cat\ 1|B)P(B)}$$

Then if $P(cat\ 1|G) \approx P(cat\ 1|B)$ we immediately have that $P(G|cat\ 1) \approx P(G)$, i.e. no extra information can be extracted from this variable.

Model performance

The aim of the modelling exercise is to find the appropriate coefficients β_i for all $i=0,1,\ldots,n$ that lead to a model that has two main desirable properties:

1. It fits the existing data
2. It can produce the correct probability of default on data that it has not seen before

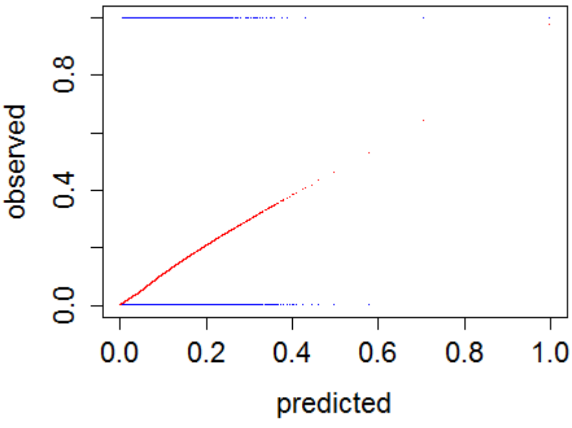
The first of these requirements is called "**Goodness-of-fit**" while the second is called "**Predictive Power**". If the data sample is sufficiently large (which it is in our case) the predictive power of the model is tested *out-of-sample* which means that we split the data set into a training set (used only for model development) and a validation set (used only for model testing). We have taken the training / validation split to be at 40%. This means that:

- 40% of Goods (no-default) are taken as validation data
- 40% of Bads (default) are taken as validation data

Such a split should be undertaken with some caution since a totally random split may result in that some of the categories in categorical variables are not well-represented.

Goodness of Fit

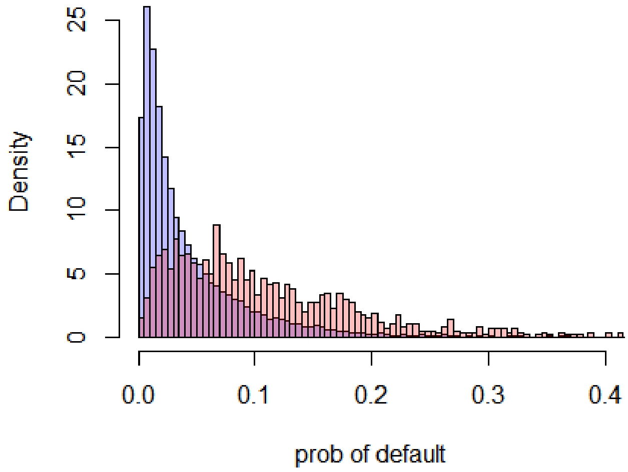
If the data contained one response variable (the probability of default) and only one explanatory variable then measuring the goodness of fit would be a trivial task: A simple graph would allow us to inspect visually the fit. However since the dimensionality of the dataset is typically very large (of the order of 50 variables) we have to resort to other methods. The first of these tests is a graph of the following type:



Blue dots correspond to the points of the data set. On the x-axis we show the model prediction of the probability of default (a real number between 0 and 1) while on the y-axis we show the actual observed value of default (an integer value of either 0 or 1). Since we cannot easily assess the density of the cloud of points as they overlap each other, we have "smoothed" the above set of data points by considering, for each value across the x-axis, an average between those that have observed=0 and those that have observed=1. The result of this smoothing process is the red line. A perfect model would have a red line equal to the diagonal, since this would imply that if (for example) the model predicts a PD of 30%, the observed value is also 30%. Therefore a deviation away from the diagonal indicates that our model does not fit the data well.

Predictive Power

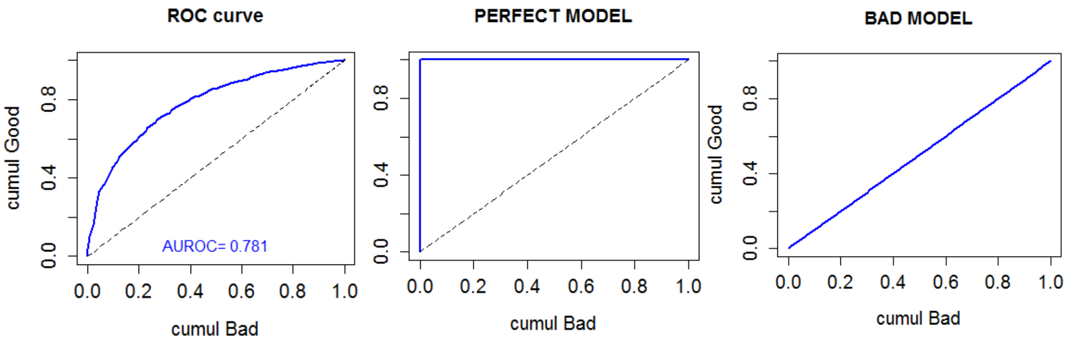
There are several ways of testing the predictive power of a model, i.e. its ability to generalise the rules it has learned from the training data set to a new (unseen) data set. The most common way is through the computation of the histograms of the defaults versus non-defaults and subsequent inspection of their overlap. To illustrate the point we show below a graph of two histograms: x-axis is the probability of default while y-axis is the density of data points with a certain probability of default. In blue are the clients which we know that have not gone in default (the "good") while in red are the clients which we know that have gone in default (the "bad"). We see that there is a significant overlap between the two histograms. This implies that if the model gives a probability of default of e.g. 5% where the two histograms are in overlap, then we cannot say with 100% certainty whether we should classify this data point as good or as bad. In the two extremes, where PD=0 or PD=1 we see that the overlap is much less and if the model produces a PD of that value then we can almost with 100% certainty classify the data point as good or as bad respectively.



Choosing the correct cut-off value of the PD, below which a client is considered "good" and above which is considered "bad", is a matter or risk-preference and there is no simple answer as to what is the correct cut-off value.

This leads to the ROC curve which includes in one graph the performance of the model for all possible cut-off values. ROC stands for "Receiver Operating Characteristic".

The ROC curve as shown below considers systematically all cut-off values for the PD from 0 to 100%. For each cut-off value it then measures the number of Goods below the cut-off and the number of Bads below the cut-off. It then plots these two numbers as x- and y-coordinates. A perfect model would show a ROC curve that consists of two straight lines: From (0,0) to (0,1) and from (0,1) to (1,1), i.e. very steep. A model with no predictive power would have a ROC curve that follows the diagonal, since that would imply that for every cut-off value we find an equal number of goods and bads, i.e. there is a perfect overlap in the two histograms.



Typically we concentrate all information of the ROC curve into one number which is chosen to be the area under the ROC curve (the perfect model has an area equal to 1). Based on experience we give below a table of ROC values and their interpretation with respect to the model appropriateness.

Predictive Power	Area Under ROC
Acceptable	>70%
Good	>80%
Very Good	>85%

Confusion Matrix

An additional measure of predictive power is the so-called confusion matrix. It has the form of the table below (which is a hypothetical example). We test the model's classification results against the actual observed classification. Of particular interest in this table is the "True Positive Rate" that corresponds to the fraction of Goods that are correctly classified [in the example below 7014/(7014+3171)) and the "True Negative Rate" that corresponds to the fraction of Bads that are correctly classified (in the example below 357/(357+178)].

	Predicted Bad	Predicted Good
Observed Bad	357	178
Observed Good	3171	7014

Based on experience we give below a table of figures that will allow us to interpret the results of the confusion matrix:

Predictive Power	TP & TN rate
Acceptable	>60%
Good	>70%
Very Good	>85%

Model refinements

There is a number of assumptions underlying the logistic regression model

$$p = \frac{\exp(\beta_0 + \beta_1 \cdot x_1 + \cdots + \beta_n \cdot x_n)}{1 + \exp(\beta_0 + \beta_1 \cdot x_1 + \cdots + \beta_n \cdot x_n)}$$

The most important of these are:

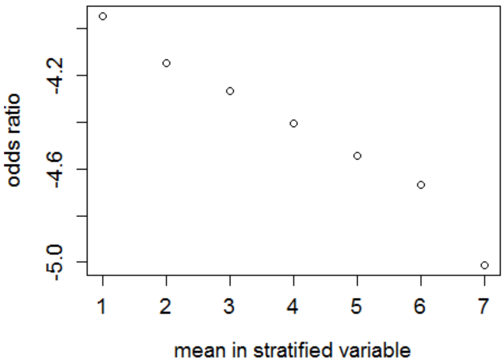
- Linearity in the explanatory variables
- Absence of interactions among explanatory variables

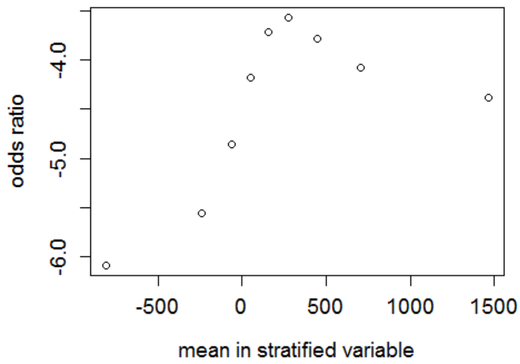
The first of these implies that inside the exponentials there are no higher-order terms, for example x_1^2. The second implies that there are no terms mixing the variables, for example $x_1 \cdot x_2$.These assumptions, however, need not be necessarily true. Their validity should be tested. Testing implies that one re-writes the logistic model slightly differently, as:

$$\ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 \cdot x_1 + \cdots + \beta_n \cdot x_n$$

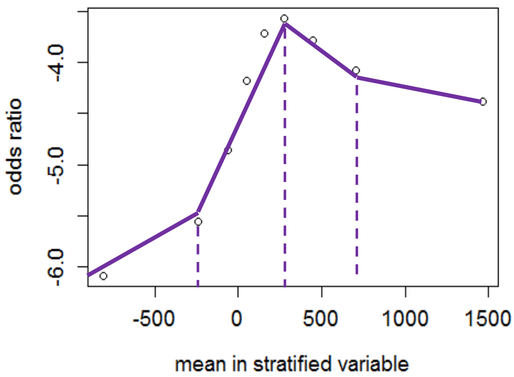
The left-hand side, named the log-odds ratio, can be computed from the model. The right-hand side is linear in the explanatory variables. This means that if the above assumptions are true one should observe a straight line for each of the explanatory variables. If the line is not straight, then the assumptions are not satisfied.

We illustrate this computation in the figures below. In the left figure, the log-odds ratio is approximately straight, implying linearity is satisfied for this variable. In the right figure, the log-odds ratio is not a straight line implying that the linearity assumption is violated.





One way to fix this problem is to create a piecewise linear function in the following way:



One can determine, by visual inspection or otherwise, the “knots”, which are the places where the various linear pieces start and end. Then the construction to impose in the logistic function concerning this variable reads:

$$Piecewise\ Function(x) = \gamma_1 \cdot \max(x - Knot_1, 0) + \gamma_2 \cdot \max(x - Knot_2, 0) + \gamma_3 \cdot \max(x - Knot_3, 0)$$

The variables γ_i are found, as before, via Maximum Likelihood.

Model interpretation

One of the most appealing features in logistic regression is the transparency in the interpretation of the model. If for simplicity we consider that the model contains only one explanatory variable then we can rewrite it as

$$\ln\left(\frac{p(x)}{1-p(x)}\right) = \beta_0 + \beta_1 \cdot x_1$$

Suppose furthermore that x is a Boolean variable. Then we obtain the two equations:

$$\ln\left(\frac{p(1)}{1-p(1)}\right) = \beta_0 + \beta_1$$
$$\ln\left(\frac{p(0)}{1-p(0)}\right) = \beta_0$$

which together lead to the neat result:

$$\frac{p(0)}{1-p(0)} = e^{\beta_1}\frac{p(1)}{1-p(1)}$$

This gives the interpretation of the coefficient β_1: It provides the change in the probability of default if the variable changes by one unit. This can help us understand how the probability of default changes if (for example) the savings capital of a client changes from 1,000 EUR to 100,000 EUR. Similarly for all other variables.

Armed with this result we can provide further guidance to the business by giving the impact of each individual explanatory variable to the client’s forecasted probability of default.

How we can help

Our team of experts provides assistance at various levels of the modelling process, from training to design to implementation, to validation.

Deloitte's data analytics solution team consists of high-calibre individuals with long-standing experience in the domain of finance and data analytics.

Some examples of solutions tailored to your needs:
- A managed service where Deloitte provides independent validation of your model at your request
- Expert assistance with the design and implementation of your own model
- A stand-alone tool
- Training on the data analytics solutions, the credit scoring model, logistic regression, statistical modelling or any other related topic tailored to your needs

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