



# Classification Restricted Boltzmann Machine for comprehensible credit scoring model



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## ABSTRACT

Credit scoring is the assessment of the risk associated with a consumer (an organization or an individual) that apply for the credit. Therefore, the problem of credit scoring can be stated as a discrimination between those applicants whom the lender is confident will repay credit and those applicants who are considered by the lender as insufficiently reliable. In this work we propose a novel method for constructing comprehensible scoring model by applying Classification Restricted Boltzmann Machines (ClassRBM). In the first step we train the ClassRBM as a standalone classifier that has ability to predict credit status but does not contain interpretable structure. In order to obtain comprehensible model, first we evaluate the relevancy of each of binary features using ClassRBM and further we use these values to create the scoring table (scorecard). Additionally, we deal with the imbalanced data issue by proposing a procedure for determining the cutting point using the geometric mean of specificity and sensitivity. We evaluate our approach by comparing its performance with the results gained by other methods using four datasets from the credit scoring domain.

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## 1. Introduction

The problem of building a decision model for identification of consumers with unsecured repayment status can be seen as an issue of training a dichotomous classifier, where the positive class (usually less numerous) represents “bad” applicants and the negative class stays behind “good” cases. Each example in training data refers to a customer described by a vector of attributes that codes the most important information about her or him in the considered credit approval context, and the corresponding class label represents the real repayment status. The main goal of the training procedure is to construct the model that will be able to correctly classify as many new clients as possible.

Unfortunately, the specificity of the problem enforces couple of limitations related to the issue of constructing decision models from data. First, according to the regulation of banking supervision, financial institutions in some countries are obliged to present a comprehensible justification in the case the credit application is denied. Therefore, the process of decision making performed by the data-based scoring model ought to be interpretable. As a consequence, only comprehensible models like scoring tables (scorecards), decision trees and rules are suitable to be used to deal with that

issue. Second, the training set used to construct decision model is usually influenced by imbalanced data phenomenon, because the data is dominated by applicants with positive credit approval. Consequently, the typical learner constructed on such data is biased toward majority class, what practically means that it has tendency to assign positive repayment status even to very risky consumers. As a result, the problem of uneven class distribution should be taken into account in the process of constructing credit scoring model.

The issue of constructing credit scoring models directly from data has been successfully studied since Durand proposed to use discriminant function to separate “good” and “bad” consumers in 1941 (Crook, Edelman, & Thomas, 2007). Current models used for the credit risk assessment utilize the machine learning techniques to increase the accuracy of prediction, to deal with the imbalanced data phenomenon, or to construct comprehensible learners. Various classification methods are considered to be used to predict credit repayment such as neural networks (West, 2000), Gaussian Processes (Huang, 2011), Support Vector Machines (SVMs) (Bellotti & Crook, 2009; Huang, Chen, & Wang, 2007), or ensemble classifiers (Nanni & Lumini, 2009). Many authors recognize the need of constructing the comprehensible models directly from data by applying rules and trees inducers (Crook et al., 2007), or indirectly, by extracting interpretable models from strong learners, so-called “black-box” classifiers, such as SVMs (Martens, Baesens, Van Gestel, & Vanthienen, 2007) or ensemble classifiers (De Bock & Van den Poel, 2012). The issue of imbalanced data in the context

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of constructing credit scoring models was also considered in the literature, i.e., adaptive, cost-sensitive version of SVM (Yang, 2007), balanced neural networks (Huang, Hung, & Jiau, 2006), or ensemble classifier with switching class labels (Zieba & Świątek, 2012).

In this work we propose a novel machine learning technique which takes advantage of Classification Restricted Boltzmann Machine (ClassRBM) to construct the credit scoring table. We use ClassRBM as a universal approximator over the binary random variables which is further applied to determine weights (scoring points) in the scoring table. Moreover, the scoring tables are the simplest models to interpret and can be easily implemented in any bank system. Additionally, our approach deals with the imbalanced data by selecting the cutting point with the highest geometric mean of specificity and sensitivity. Unlike standard methods, our approach combines issues which are typically considered separately: (i) it makes use of the strong classifier (ClassRBM), (ii) it deals with the uneven class distribution problem, and (iii) it constructs highly comprehensible and easy-to-implement scoring model.

This work is organized as follows. In Section 2 Classification Restricted Boltzmann Machine is introduced, the procedure of constructing credit scoring table using this model is presented and the procedure for determining the cutting point for imbalanced data is outlined. In Section 3 the quality of the presented approach is examined by comparing its performance to state-of-the-art methods using the datasets from the credit scoring domain. This paper is summarized by conclusions in Section 4.

## 2. Methodology

In this section we present novel method to construct the scoring table basing on the trained Classification Restricted Boltzmann Machine (ClassRBM). In the first part of this section we introduce the ClassRBM as a standalone classifier which allows to use the probabilistic framework to evaluate the relevancy of the binary attributes. Further, we present a method for constructing comprehensible credit scoring model using the class-dependent importance of each of the attributes indicated by ClassRBM. Finally, we describe the procedure to determine the cutting point by maximizing the geometric mean of the specificity and the sensitivity on training data.

### 2.1. Classification Restricted Boltzmann Machine

#### 2.1.1. Model definition

ClassRBM (Larochelle & Bengio, 2008; Larochelle, Mandel, Pascanu, & Bengio, 2012) is a three-layer undirected graphical model where the first layer consists of visible input variables  $\mathbf{x} \in \{0, 1\}^D$ , the second layer consists of hidden variables (units)  $\mathbf{h} \in \{0, 1\}^M$ , and the third layer represents observable output variable  $y \in \{1, 2, \dots, K\}$ . We use the 1-to- $K$  coding scheme which results in representing output as a binary vector of length  $K$  denoted by  $\mathbf{y}$ , such that if the output (or class) is  $k$ , then all elements are zero except element  $y_k$  which takes the value 1. We allow only the inter-layer connections, i.e., there are no connections within a layer.

With each state  $(\mathbf{x}, \mathbf{y}, \mathbf{h})$  we associate the energy given by the following equation:

$$E(\mathbf{x}, \mathbf{y}, \mathbf{h}|\theta) = -\mathbf{b}^\top \mathbf{x} - \mathbf{c}^\top \mathbf{h} - \mathbf{d}^\top \mathbf{y} - \mathbf{x}^\top \mathbf{W}^1 \mathbf{h} - \mathbf{h}^\top \mathbf{W}^2 \mathbf{y} \quad (1)$$

with parameters  $\theta = \{\mathbf{b}, \mathbf{c}, \mathbf{d}, \mathbf{W}^1, \mathbf{W}^2\}$ . A ClassRBM with  $M$  hidden units is a parametric model of the joint distribution of visible and hidden variables, that takes the following form:

$$p(\mathbf{x}, \mathbf{y}, \mathbf{h}|\theta) = \frac{1}{Z(\theta)} \exp\{-E(\mathbf{x}, \mathbf{y}, \mathbf{h}|\theta)\} \quad (2)$$

where

$$Z(\theta) = \sum_{\mathbf{x}, \mathbf{y}, \mathbf{h}} \exp\{-E(\mathbf{x}, \mathbf{y}, \mathbf{h}|\theta)\} \quad (3)$$

is a partition function.

The advantage of the ClassRBM is that crucial conditional probabilities which are further used in the inference can be calculated analytically (Larochelle & Bengio, 2008; Larochelle et al., 2012)<sup>1</sup>:

$$p(\mathbf{x}|\mathbf{h}) = \prod_i p(x_i|\mathbf{h}) \quad (4)$$

$$p(x_i = 1|\mathbf{h}) = \text{sigm}(b_i + \mathbf{W}_i^1 \mathbf{h}) \quad (5)$$

$$p(y_k = 1|\mathbf{h}) = \frac{\exp\{d_k + (\mathbf{W}_k^2)^\top \mathbf{h}\}}{\sum_l \exp\{d_l + (\mathbf{W}_l^2)^\top \mathbf{h}\}} \quad (6)$$

$$p(\mathbf{h}|y_k = 1, \mathbf{x}) = \prod_j p(h_j|y_k = 1, \mathbf{x}) \quad (7)$$

$$p(h_j = 1|y_k = 1, \mathbf{x}) = \text{sigm}(c_j + (\mathbf{W}_j^1)^\top \mathbf{x} + W_{jk}^2) \quad (8)$$

where  $\text{sigm}(\cdot)$  is the logistic sigmoid function,  $\mathbf{W}_i^1$  is  $i$ th row of weights matrix  $\mathbf{W}^1$ ,  $\mathbf{W}_j^1$  is  $j$ th column of weights matrix  $\mathbf{W}^1$ ,  $W_{ij}^1$  is the element of weights matrix  $\mathbf{W}^1$ .

An important advantage of the ClassRBM is that for enough number of hidden units this model can represent any distribution over binary vectors and its likelihood can be improved by adding new hidden units, unless the generated distribution already equals the training distribution (Le Roux & Bengio, 2008; Martens, Chattopadhyaya, Pitassi, & Zemel, 2013). This is a significant fact because we have (at least theoretical) assurance that the ClassRBM is a universal approximator for distributions over binary inputs.

For the considered problem of credit repayment the vector of binary inputs  $\mathbf{x}$  represents the characteristics which describe the applicant and the output vector  $\mathbf{y}$  stays behind the credit decision variant. Therefore, the vector of the hidden units allows to approximate the distribution over the entire space representing credit applicants.

#### 2.1.2. Prediction

For given parameters  $\theta$  it is possible to compute the distribution  $p(y|\mathbf{x}, \theta)$  which can be further used to choose the most probable class label. This conditional distribution takes the following form (Larochelle & Bengio, 2008; Larochelle et al., 2012):

$$p(y_k = 1|\mathbf{x}, \theta) = \frac{\exp\{d_k\} \prod_j (1 + \exp\{c_j + (\mathbf{W}_j^1)^\top \mathbf{x} + W_{jk}^2\})}{\sum_l \exp\{d_l\} \prod_j (1 + \exp\{c_j + (\mathbf{W}_j^1)^\top \mathbf{x} + W_{jl}^2\})} \quad (9)$$

Notice that the ClassRBM can be used as a standalone classifier to predict the credit repayment status. However, because it is hard-to-interpret “black box” model, it is rather unlikely to be used as a credit scoring model.

#### 2.1.3. Learning

The key issue in the ClassRBM is the choice of a learning procedure. We assume given  $N$  data,  $\mathcal{D} = \{\mathbf{x}_n, y_n\}$ , and the likelihood function as the objective. However, in order to train ClassRBM we may consider two approaches. The first one, called *generative approach*, aims at maximizing the likelihood function for joint distribution  $p(\mathbf{x}, \mathbf{y}|\theta)$ . The second one, which we refer to as *discriminative approach*, considers the likelihood function for conditional distribution  $p(\mathbf{y}|\mathbf{x}, \theta)$ . The generative approach in the context of the ClassRBM is troublesome because exact gradient of the likelihood function for joint distribution cannot be calculated analytically, and only an approximation can be applied, e.g.,

<sup>1</sup> Further in the paper, sometimes we omit explicit conditioning on parameters  $\theta$ .

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