Neural Network Survival Analysis for Personal Loan Data

Article *in* Journal of the Operational Research Society · December 2004
DOI: 10.1057/palgrave.jors.2601990 · Source: RePEc

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WORKING PAPER

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November 2004

2004/281

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D/2004/7012/67

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Abstract. Traditionally, credit scoring aimed at distinguishing good payers from bad payers at the time of the application. The timing when customers default is also interesting to investigate since it can provide the bank with the ability to do profit scoring. Analysing when customers default is typically tackled using survival analysis. In this paper, we discuss and contrast statistical and neural network approaches for survival analysis. Compared to the proportional hazards model, neural networks may offer an interesting alternative because of their universal approximation property and the fact that no baseline hazard assumption is needed. Several neural network survival analysis models are discussed and evaluated according to their way of dealing with censored observations, time-varying inputs, the monotonicity of the generated survival curves and their scalability. In the experimental, we contrast the performance of a neural network survival analysis model with that of the proportional hazards model for predicting both loan default and early repayment using data from a U.K. financial institution.

Keywords: credit scoring, survival analysis, neural networks

Introduction

Traditionally, the primary goal of credit scoring was to distinguish good customers from bad customers without taking into account when customers tend to default [1,2]. The latter issue is however becoming more and more a key research question since the whole process of credit granting and repayment is being more and more conceived as dynamic instead of static. The advantages of having models that estimate when customers default are [3,4]

- the ability to compute the profitability over a customer's lifetime and perform profit scoring;
- these models may provide the bank with an estimate of the default levels over time which is useful for debt provisioning;
- the estimates may help to decide upon the term of the loan;
- changes in economic conditions can be easier incorporated.

Until now, not many authors have addressed the issue of predicting customer default times. Narain was one the first authors to use survival analysis methods for credit scoring [5]. He analysed a data set of 1242 applicants accepted for a 24 month loan between mid 1986 and mid 1988. The data was analysed using the Kaplan-Meier method and by fitting exponential regression models. It was shown that the results obtained are encouraging and reasonable.

Banasik et al. report on the use of the proportional hazards model for predicting when borrowers default or pay off early [3]. They use personal loan data from a major U.K. financial institution which consists of application information of 50000 loans accepted between June 1994 and March 1997 together with their monthly performance description for the period up to July 1997. The data was analysed using the non-parametric proportional hazards model (no baseline hazard assumption), two parametric proportional hazards models using exponential and Weibull baseline hazards, and an ordinary logistic regression approach. Stepanova and Thomas continued the research by Banasik et al.

augmenting the performance of the estimated proportional hazards models by using a new way of coarse-classifying the characteristics and by including time-by-characteristic interactions[6].

Stepanova and Thomas perform behavioral scoring using PHAB (proportional hazards analysis behavior scores) models[7]. The authors conclude by saying that the PHAB scores are useful as indicators of both risk and profit.

Although the proportional hazards model is the most frequently used model for survival analysis, it still suffers from a number of drawbacks. If complex (non-linear) terms are to be included (e.g. interaction terms between inputs, quadratic terms, ...), they must be specified somewhat arbitrarily by the user[8]. Furthermore, in the standard proportional hazards model, the baseline hazard function is assumed to be uniform across the entire population resulting in proportional hazards. Although time-varying inputs and stratification allow for non-proportionality, these extensions might not provide the best way to model the baseline variation[8,9]. In this paper, we will discuss how neural networks may offer an answer to these problems. This will be investigated in a credit scoring context by studying when customers tend to default or pay off their loan early.

This paper is organised as follows. In section 2, we briefly discuss the proportional hazards model. Section 3 presents a literature overview on the use of neural networks for survival analysis. The empirical setup and the results are reported in section 4. Section 5 concludes the paper.

The proportional hazards model for survival analysis

The aim of survival analysis is to estimate the distribution of the event times $f(t)$ of a group of subjects. This is usually done by specifying two other mathematically equivalent functions, the survival function $S(t)$ and the hazard function $h(t)$ defined as follows[10,11]:

$$S(t) = P(T > t) = \int_t^\infty f(u)du = 1 - F(t) \tag{1}$$

$$h(t) = \lim_{\Delta t \to 0} \frac{P(t \leq T < t + \Delta t | T \geq t)}{\Delta t}, \tag{2}$$

whereby $F(t)$ represents the cumulative distribution function. The survival function models the probability that a subject will survive time period t. It is a monotone decreasing function of t with $S(0) = 1$ and $S(\infty) = 0$. Since time is continuous, the probability that an event will take place exactly at time t is 0. Hence, the hazard looks at the probability of an event occurring in time interval t to $t + \Delta$t, given that the subject has survived to t. However, this probability increases with Δt, and this is compensated by dividing by Δt. Taking the limit for $\Delta t \to 0$, the hazard function tries to quantify the instantaneous risk that an event will occur at time t given that the subject has survived to time t.

The Kaplan-Meier (KM) or product limit estimator is the non-parametric maximum likelihood estimator of the survival function $S(t)$ [12]. When censoring is present, we start by ordering the event times in ascending order, $t_{(1)} < t_{(2)} < ... < t_{(k)}$. The maximum likelihood KM estimator for the survival function then becomes[12]:

$$\hat{S}(t) = \prod_{j|t_{(j)} \leq t} (\frac{n_j - d_j}{n_j}) = \prod_{j|t_{(j)} \leq t} (1 - \frac{d_j}{n_j}) = \hat{S}(t-1)(1 - \frac{d_t}{n_t}) \tag{3}$$

where d_j is the number of subjects with event time $t_{(j)}$ and n_j is the total number of subjects at risk at time $t_{(j)}$.

Parametric survival analysis models approximate the lifetime distribution $f(t)$ by using popular distribution functions e.g. the exponential, Weibull and Gompertz distribution [10,11].

The most commonly used model for survival analysis is the Cox proportional hazards model. The proportional hazards model (also called the Cox model) allows for the inclusion of explanatory inputs which may influence the survival time. In its most general form, the model is as follows[10,11]:

$$h(t, \mathbf{x}_i) = h_0(t) g(\boldsymbol{\beta}^T \mathbf{x}_i). \tag{4}$$

Cox suggested to replace $g(\boldsymbol{\beta}^T \mathbf{x}_i)$ by $\exp(\boldsymbol{\beta}^T \mathbf{x}_i)$ such that the model becomes:

$$h(t, \mathbf{x}_i) = h_0(t) \exp(\boldsymbol{\beta}^T \mathbf{x}_i), \tag{5}$$

which is the most widely used variant. This equation says that the hazard for a subject i at time t is the product of an unspecified, positive baseline hazard function $h_0(t)$, and a linear function of a vector of inputs $\mathbf{x}_i$ which is exponentiated. The baseline hazard $h_0(t)$ is a function of time only, and is assumed to be the same for all subjects. The name proportional hazard stems from the fact that the hazard of any individual is a fixed proportion of the hazard of any other individual over time. The $\boldsymbol{\beta}$ parameters of the proportional hazards model can be estimated without having to specify the baseline hazard function $h_0(t)$. Therefore, the proportional hazards model is often called a semi-parametric model. The estimation of the $\boldsymbol{\beta}$ coefficients is done by using the partial likelihood principle [10,11].

Neural Networks for Survival Analysis

Direct Classification

The simplest method considers survival for a fixed time period, and consequently gives a binary classification problem[13]. Censored observations are removed and biases are introduced. The neural network output then provides an estimate of the probability that a subject will survive the time period. Above the 50% threshold, the subject is assumed to survive the period. It is clear that this approach is rather basic and does not allow to produce individual survival or hazard curves. Furthermore, it does not deal with the problem of censoring and time-varying inputs.

Ohno-Machado

Ohno-Machado[14] uses multiple neural networks to solve the survival analysis problem. Each neural network has a single output predicting survival at a certain time point. The networks are then trained using their own data subsets consisting of cases that made it to the corresponding time period. Censored observations are included until their time of censoring. Hence, the number of training instances gradually decreases for the later time intervals making the predictions less reliable. The author argues that when using these neural networks in isolation, non-monotonic survival curves may result. As a result, the

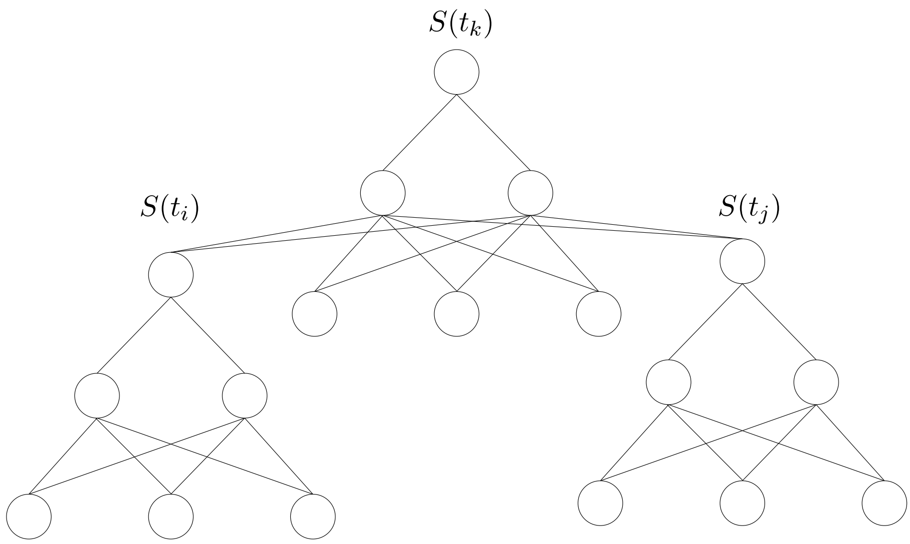


Figure 1: An example of a modular neural network for survival analysis whereby the output of the networks predicting $S(t_i)$ and $S(t_j)$ are used as additional inputs for the network predicting $S(t_k)$.

probability of a person surviving two periods could be greater than the probability to survive one period because the interdependencies of the survival probabilities over time are not properly taken into account when isolated neural networks are used. The author describes a way to decrease the frequency of non-monotonic curves by combining the neural networks. Survival predictions of one neural network are then used as an additional input to another neural network as illustrated in Figure 1. However, it is still possible to obtain non-monotonic survival curves although the departure from monotonicity is smaller than if the neural networks were not connected to each other. Furthermore, the issue of how to combine the neural networks remains an open question. The necessity to use multiple neural networks and the question how to combine them represent an important scalability problem which makes the method less suitable for handling large data sets.

Ravdin and Clark

Ravdin and Clark[15] use a multi-layer feed-forward neural network with a single output unit representing the survival status. A time indicator and a survival status indicator are added to each record. The time indicator then records the successive time periods $[1, T_{max}]$ for which a prediction is to be made, with T_{max} the maximum time of follow-up. An uncensored input is then replicated T_{max} times whereas a censored input is replicated t times with t being the time of censoring. The survival status is the target of the network and is set to zero as long as the subject is alive and to 1 otherwise. Although time dependent inputs were not discussed in the original study, they can be easily included into the corresponding data records. The authors state that the output of the neural network (referred to as the prognostic index) is roughly proportional to the Kaplan-Meier estimate of the survival probability. However, they provide no guarantees that the generated survival curves will be monotonically decreasing. Furthermore, the replication of records introduces two problems. First, it will result in large biases because the number of deaths in the late time intervals will be overrepresented. The authors suggest to handle this by selective sampling such that the proportion of deaths matches the Kaplan-Meier estimate. Second, while this method does not require the use of multiple networks, it will result in very large data sets, which causes severe scalability problems.

Biganzoli et al.

A variation on the approach of Ravdin and Clark was suggested by Biganzoli et al.[16]. They also train a neural network with one output and an additional time indicator input. However, unlike Ravdin and Clark, uncensored subjects are only replicated for the time intervals in which they were actually observed. Hence, subjects that have died are not included after the time interval of death. Again, time dependent inputs might be easily included since each subject has multiple input vectors which may change across the intervals of observation. The neural network predicts discrete hazard rates which may be easily converted to monotone survival probabilities. However, the approach is not scalable because of the enormous data replication requirements.

Lapuerta et al.

Lapuerta et al.[17] suggest a multi-network strategy to impute the survival times for the censored cases. For each time period considered, a separate neural network is constructed. These networks are trained using only the observations for which the survival status for the corresponding time period is known. Subsequently, the trained networks are used to predict the outcome for the censored cases. The non-censored and imputed censored observations are then provided for training the principal neural network (referred to as the Predictor network in the original paper) which predicts the probability of survival for each time period considered. Although the proposed method compares favorably to the Cox proportional hazards model, no guarantees are provided that the derived survival probabilities are monotonically decreasing and time varying inputs are also not allowed. Furthermore, it is clear that this approach is not suitable for large-scale applications since one needs to train as many neural networks as there are time periods considered.

Faraggi

Faraggi[18] proposes a neural network variant of the Cox proportional hazards model reported in (5) by replacing the linear function $\boldsymbol{\beta}^T\mathbf{x}_i$ by the output $g(\mathbf{x}_i, \boldsymbol{\theta})$ of a neural network with a single, logistic hidden layer and a linear output layer

$$h(t, \mathbf{x}_i) = h_0(t) \exp[g(\mathbf{x}_i, \boldsymbol{\theta})]. \tag{6}$$

Analogous to the Cox model, no bias input is considered for the output layer since this is implicitly incorporated into the baseline hazard $h_0(t)$. The $\boldsymbol{\theta}$ parameters are then also estimated using the partial likelihood principle and Newton-Raphson optimization. The approach was applied in a breast cancer study in[19]. This method allows to preserve all the advantages of the classical proportional hazards model. However, the standard approach still assumes that the hazards are proportional. Although time-varying covariates and/or stratification might allow for non-proportionality, these extensions may not be the best way to model the baseline variation.

Street

Street[20] uses a multilayer perceptron with T_{max} output units to tackle the survival analysis problem, whereby T_{max} represents the maximum time horizon of the study. A hyperbolic tangent activation function is used in the output layer such that all output neurons take on values between -1 and $+1$. The first output neuron having a value < 0 is considered to be the output neuron that predicts the event time. If all output neurons have values > 1, then the patient is considered to survive the entire time period of the study. The output units thus represent the survival probability for the corresponding time period.

For the non-censored cases, the output values are set to $+1$ as long as the patient is alive and to -1 thereafter. For the censored cases, the output units are also set to $+1$ until their censoring time. After this period, Street uses the Kaplan-Meier estimates of (3)

$$S(t) = S(t-1) \times (1 - h(t)), \tag{7}$$

with $h(t) = \frac{d_t}{n_t}$, whereby d_t represents the number of deaths in period t, and n_t represents the subjects at risk in that period. The latter number is calculated by subtracting from the number of subjects at risk at the beginning of period $t-1$, the total number of deaths and the total number of censored observations in that same period. The Kaplan-Meier hazards are then used to compute the survival probability of the censored observations after the censoring time. Note that these probabilities are then scaled to the range of the hyperbolic tangent function in the following way: $activation = 2 \times probability - 1$. In summary, the outputs of the training set observations are encoded as follows:

$$S(t) = \begin{cases} 1 & 1 \leq t \leq L \\ -1 & D = 1 \ \ and \ \ L < t \leq T_{max} \\ S(t-1) \times (1 - h(t)) & D = 0 \ \ and \ \ L < t \leq T_{max}, \end{cases} \tag{8}$$

whereby T_{max} represents the maximum number of time periods involved in the study, L the subject lifetime or censoring time, and D indicates if the subject is censored ($D = 0$) or not ($D = 1$). The individual survival curve of an observation can then be derived based on the activation values of the output units. Since the neural network cannot be forced to generate monotonically decreasing output units, a non-monotone survival curve is still possible, which complicates its interpretation[9]. Furthermore, no extension is provided to deal with time-varying inputs.

Mani

A variation on the method of Street was developed by Mani[9]. Again, for every observation in the training set, T_{max} output units are computed. Nevertheless, these output units now represent the hazard rate instead of the survival probabilities that were used in the approach of Street. The outputs are then computed as follows:

$$h(t) = \begin{cases} 0 & 1 \leq t \leq L \\ 1 & D = 1 \ \ and \ \ L < t \leq T_{max} \\ \frac{d_t}{n_t} & D = 0 \ \ and \ \ L < t \leq T_{max} \end{cases} \tag{9}$$

Again, T_{max} represents the maximum number of periods involved in the study, L the subject lifetime or censoring time, and D indicates if the subject is censored ($D = 0$) or not ($D = 1$). For uncensored observations, the hazard is set to zero until the time of death and 1 thereafter. For censored observations, the hazard is set to zero until censoring time and to the Kaplan-Meier estimate thereafter. The survival probabilities may then be estimated by using (3). The generated survival curves will thus be monotonically decreasing which simplifies the interpretation and increases robustness[9]. However, the topic of time-varying inputs has been left unaddressed.

Brown et al.

Analogous to Mani, Brown suggests a single neural network with multiple outputs to predict hazard rates[21]. For the non-censored observations, the network output is set to 0 as long as the subject is alive and to 1 when the subject undergoes the event. For the time intervals following the event, the hazard is unconstrained. The output values for the censored observations are set to 0 until the time of censoring and are unconstrained for all subsequent time intervals. The authors then suggest to train the neural network to minimize the sum of squared error criterion and to perform no weight updates when the hazard is unconstrained by setting the corresponding errors to 0. The approach presented is scalable and results in monotonic survival curves. Again, no extension is presented to deal with time-varying inputs.

Discussion

Table 1 presents an overview of the characteristics of the neural network based methods for survival analysis discussed in the previous subsections. From the literature review above, it becomes clear that for large scale data sets, the approaches of Faraggi, Mani and

	Multiple NN	**Single Output**	**Monotone survival curve**	**Censoring**	**Time-varying covariates**	**Scalable**
Direct classification[13]	N	Y	N	N	N	Y
Ohno-Machado[14]	Y	Y	N	Y	Y	N
Ravdin and Clark[16]	N	Y	N	Y	Y	N
Biganzoli et al.[22]	N	Y	Y	Y	Y	N
Lapuerta et al.[17]	Y	N	N	Y	N	N
Faraggi[18]	N	Y	Y	Y	Y	Y
Street[20]	N	N	N	Y	N	Y
Mani[9]	N	N	Y	Y	N	Y
Brown[21]	N	N	Y	Y	N	Y

Table 1: Characteristics of neural network survival analysis methods.

Brown seem the most interesting. All three allow to generate monotonically decreasing survival curves and only one neural network needs to be trained. Although the approach of Faraggi also allows for time-varying inputs, it is less flexible in modeling the baseline variation. On the other hand, while the approaches of Mani and Brown allow for flexible baseline modeling, they do not solve the problem of time-varying inputs.

Empirical Evaluation

Experimental Setup and Data Set Characteristics

The statistical and neural network survival analysis techniques were applied to personal loan data from a major U.K. financial institution. All customers are U.K. borrowers who had applied to the bank for a loan. The data set consisted of the application information of 50000 personal loans, together with the repayment status for each month of the observation period of 36 months. Application characteristics available in the data set are summarized in Table 2. The status variable indicated which loans were bad, paid off to term, paid off early, or still open. We note that the same data was also used in[6]. However, we took a subsample of 15000 observations and only considered loans having a duration of less than 36 months. The few missing values were imputed using the mean for the continuous attributes and the most frequent category for the categoric attributes. The data was randomly split into a training set (10000 observations) and a test set (5000 observations). Table 3 describes the various purposes of the loans.

Figure 2 depicts the Kaplan-Meier curves for both loan default and early repayment. Note that in the default case, the Kaplan-Meier curve is very flat at the beginning since our definition of a default is three months of payments missed and thus no defaults occur during the first three months.

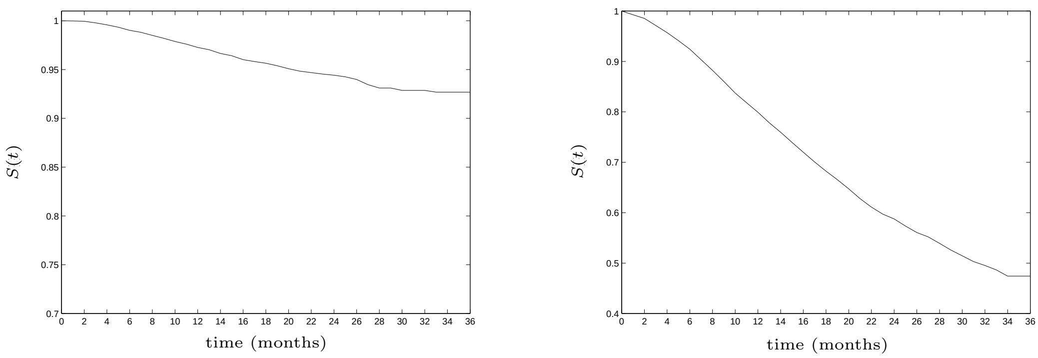
In the following subsections, we will investigate the use of statistical and neural network survival analysis techniques for predicting both early repayment and loan default. For the former, we considered all loans that are paid off early as failures and all other loans as censored whereas in the latter case all defaulted loans are failures and the remaining ones censored[3,6]. For the statistical approaches, we will experiment with the standard Cox

Number	Characteristic
1	Customer Age
2	Amount of Loan
3	Years at Current Address
4	Years with Current Employer
5	Customer Gender
6	Number of Dep. Children
7	Frequency paid
8	Home Phone Number Given
9	Insurance Premium
10	Loan type (single or joint)
11	Marital Status
12	Term of Loan
13	Home Ownership
14	Purpose of Loan

Table 2: Data set characteristics.

Number	Purpose
1	Account standard
2	Caravan
3	New Car
4	Car Repair
5	Electrical
6	General Living
7	Home Improvement
8	Honeymoon
9	Motor Caravan
10	Mixed Purchases
11	Others
12	Redecoration
13	Remortgages
14	Weddings
15	Boat
16	Motor Cycle
17	Car Over 3Yr Old
18	Car Under 3Yr Old
19	Furniture
20	Graduate Loan
21	Holiday
22	Kitchen Units
23	Musical Instrument
24	Other Specific
25	Other Vehicles
26	Refinance
27	Van

Table 3: The purpose attribute.



(a) KM curve for default

(b) KM curve for early repayment

Figure 2: Kaplan Meier curves for default and early repayment.

model of equation 5 using both the Breslow and the Efron approximations as well as with a discrete variant thereof[11]. The p-values will be used to decide upon the importance of an input. The statistical survival analysis approaches will be implemented using proc phreg in SAS^{TM}[10].

For the neural network analyses, we will adopt a variant of the approach suggested by Mani (see subsection). In order to generate monotonically decreasing survival curves, we will train the neural network to predict hazard rates and transform these to survival probabilities using equation 3. Figure 3 depicts how the outputs of the neural network are encoded. For the good customers, the output is set to zero until the last point of

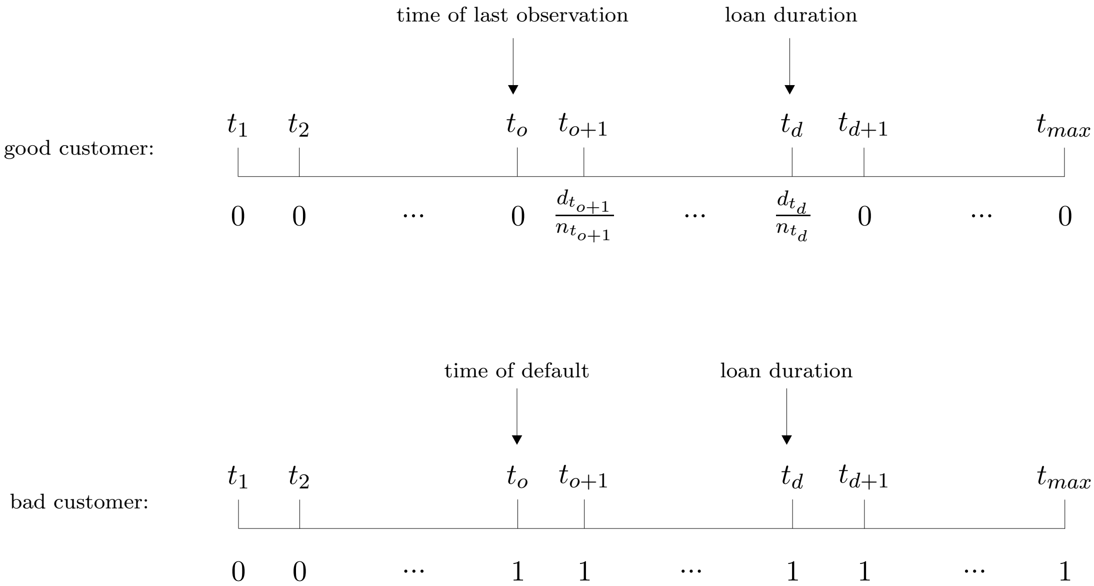


Figure 3: Encoding of the neural network outputs for survival analysis.

observation, to the Kaplan-Meier hazard until the term of the loan, and to 0 until the last time period considered. For the bad customers, we set the output to zero until the time of loan default and to 1 for all subsequent time periods. Concerning the architecture of the neural network, we use one hidden layer influenced by theoretical works which show that NNs with one hidden layer are universal approximators capable of approximating any continuous function to any desired degree of accuracy on a compact interval[23]. The hidden neurons have hyperbolic tangent transfer functions and the output neurons logistic transfer functions. The number of hidden neurons is determined by experimental evaluation. Using a cross-validation based procedure on the training data, the number of hidden neurons was varied from 1 to 20 in steps of 2. The network giving the best cross-validation performance was then retrained on the entire training data set and evaluated on the test set. We will train the networks using the evidence framework of MacKay[24,25]. This will allow us to decide upon the relevance of the inputs in a straightforward way[25].

Measuring the performance of a survival analysis model is not a trivial exercise. Following Banasik et al.[3] and Stepanova and Thomas[6], we will compare the performance of the survival analysis models by looking at the following criteria:

1. Estimating which loans will be paid off early or default within the first 12 months.

2. Estimating which loans, which are still repaying after 12 months, will pay off early or default within the next 12 months.

Remember that when no time-varying inputs are present, the proportional hazards model assumes that the customers most at risk at any one time remain the customers most at risk at all other times. Note that this does not automatically imply that the same customers will be labelled as failed (paid off early or defaulted) under each of the above criteria since for the second criterion some of the customers that failed in the first 12 months will not be considered[3].

Results for Predicting Early Repayment

Before starting the analysis, we first grouped the categorical purpose attribute into three categories by considering the probability of early repayment for each loan purpose (see

Table 4). The loan purposes having lowest probability of early repayment were categorized as low risk, those having medium probability of early repayment as medium risk, and the rest as high risk. Each category is then encoded using binary dummy variables. We compare the performance of the statistical and neural network survival analysis models with the performance of a logistic regression classifier. Taking into account the performance criteria discussed in the previous subsection, we estimate two logistic regression classifiers: one where the bads are all the loans that defaulted in the first 12 months and one where only loans that survived the first 12 months are considered and the bads are the ones that defaulted before 24 months. Table 5 presents the confusion matrix numbers of the

Low Risk	**Medium Risk**	**High Risk**
Graduate Loan	Home Improvement	Car Repair
Holiday	Other Specific	Car Over 3Yr Old
Van	Boat	General Living
Electrical	Others	Remortgages
New Car	Caravan	Mixed Purchases
Redecoration	Car Under 3Yr Old	Musical Instrument
Honeymoon	Weddings	Motor Cycle
Kitchen Units	Refinance	Motor Caravan
Other Vehicles	Furniture	Account standard

Table 4: Grouping the purpose attribute for predicting early repayment.

logistic regression model, the Cox proportional hazards model and the neural network on the test set. For the logistic regression classifier, we chose the cut-off to map the output probabilities to class labels such that the predicted number of early repayments equals the actual number of early repayments on the test set[1]. For the Cox and neural network survival analysis models, we labelled the observations having the lowest S(12) as early repaid again taking care that the predicted number of early repayments equals the actual number of early repayments on the test set. The neural network trained had one hidden layer with 10 hidden neurons.

It can be observed from Table 5 that the logistic regression classifier achieved a classification accuracy of 69.08%, the Cox model 69.72% and the neural network 70.36% on

[1]We also investigated the impact on the results if we would have chosen these cut-offs based on the training data. The resulting cut-offs varied only marginally, and the predicted number of early repayments varied only very slightly from the actual number of early repayments on the test set, hence having no impact on the results.

	Actual	Logit	Cox	NN
G-predicted G	4020	3247	3263	3279
G-predicted B	0	773	757	741
B-predicted G	0	773	757	741
B-predicted B	980	207	223	239
Attr. most imp.		term	term	insurance premium
Attr. 2nd most imp.		amount	low risk purp	medium risk purp
Attr. 3rd most imp.		low risk purp	years at address	high risk purp

Table 5: Predicting early repayment in first 12 months.

the test set. The McNemar test indicated that the performance difference between the NN and the logistic regression classifier was significant. The neural network and the Cox model gave statistically the same performance. The logistic regression and Cox model consider the term input as the most important whereas the neural network ranks the insurance premium as most relevant.

Table 6 reports the results for predicting early repayment between 12 and 24 months on the test set. For the survival analysis models, we hereto calculated $S(24)/S(12)$ and labelled the observations with the lowest value for this ratio as early repaid between 12-24 months again respecting the sample proportions. For the second performance measure,

	Actual	Logit	Cox	NN
G-predicted G	2074	1661	1612	1639
G-predicted B	0	413	462	435
B-predicted G	0	413	462	435
B-predicted B	557	144	95	122

Table 6: Predicting early repayment 12-24 months.

the logistic regression classifier achieved a classification accuracy of 68.60%, the Cox model 64.88% and the NN 66.93%. The superiority of the NN model with respect to the Cox model was significant according to the McNemar's test. Note that the performance improvement of the neural network when compared to the Cox model is only present for the second criterion and not for the first. Although, for the second criterion, it is inferior when compared to the logistic regression classifier, it has to be mentioned that the comparison is not completely fair since two separate logistic regression classifiers were trained each specifically tailored to the desired performance objective. Furthermore, also remember that the logistic regression classifier only provides a classification decision whereas the

Cox and neural network models also provide information upon the timing of the event.

To investigate the effect of each continuous variable, surface plots were generated from the neural network by fixing the remaining continuous variables to their median values and the categorical variables to their modal category. E.g., Figure 4, clearly illustrates that the survival probability for early repayment increases with decreasing customer age.

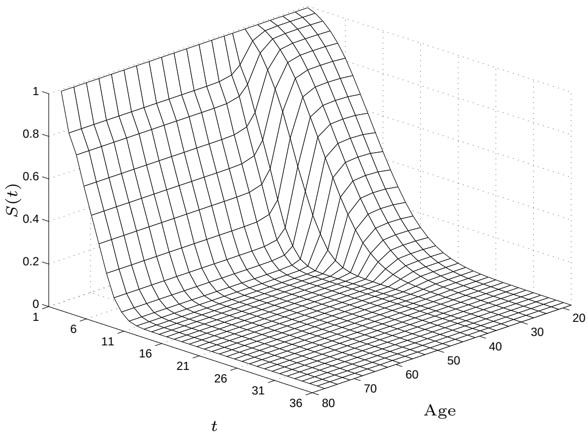


Figure 4: Evolution of neural network survival probability with respect to age for predicting early repayment.

Results for Predicting Default

Since the most risky purposes for predicting early repayment, are not necessarily the same as for predicting default, we again start by dividing the purpose attribute into 3 categories (see Table 7). Table 8 presents the confusion matrix numbers for predicting default in

Low Risk	**Medium Risk**	**High Risk**
Account standard	Electrical	Mixed Purchases
Honeymoon	Caravan	Furniture
Motor Caravan	Weddings	Car Under 3Yr Old
Boat	New Car	General Living
Graduate Loan	Home Improvement	Other Vehicles
Kitchen Units	Other Specific	Car Repair
Van	Others	Refinance
Motor Cycle	Musical Instrument	Redecoration
Holiday	Car over 3Yr Old	Remortgages

Table 7: Grouping the purpose attribute for predicting default.

the first 12 months on the test set. The neural network had 8 hidden neurons. The

	Actual	Logit	Cox	NN
G-predicted G	4870	4750	4750	4752
G-predicted B	0	120	120	118
B-predicted G	0	120	120	118
B-predicted B	130	10	10	12
Attr. most imp.		medium risk purp	medium risk purp	term
Attr. 2nd most imp.		low risk purp	low risk purp	medium risk purp
Attr. 3rd most imp.		years employed	years employed	years employed

Table 8: Predicting default in first 12 months.

logistic regression classifier and the Cox model gave the same results. The neural network performed not significantly better. Note that the logistic regression classifier and the Cox model ranked the same 3 attributes as most important. Table 9 presents the results for predicting default in 12-24 months on the test set. The Cox and NN model yielded the

	Actual	Logit	Cox	NN
G-predicted G	2567	2506	2509	2509
G-predicted B	0	61	58	58
B-predicted G	0	61	58	58
B-predicted B	64	3	6	6

Table 9: Predicting default 12-24 months.

same performance which was marginally but not significantly better than the performance of the logistic regression classifier. When looking at the results depicted in Tables 8 and 9, it becomes clear that, for predicting default, the NN models give statistically the same performance as the Cox model. One of the reasons behind this phenomenon might be that in the default case, the data is more skewed since only 130 customers of the 5000 actually defaulted in the first twelve months (2.6%) and only 64 of the 2631 defaulted between 12 and 24 months (2.4%). For that reason, we also conducted the experiments on a second default data set whereby we oversampled the number of defaults. Table 10 presents the results for predicting default in the first 12 months on the oversampled data set. The neural network had 16 hidden neurons. The logistic regression classifier yielded the best performance followed by the Cox model and the neural network. The performance differences were however not statistically significant. Observe how all three models agree on the importance of the number of years employed in predicting loan default. Table 11

	Actual	Logit	Cox	NN
G-predicted G	4208	3688	3683	3677
G-predicted B	0	520	525	531
B-predicted G	0	520	525	531
B-predicted B	792	272	267	261
Attr. most imp.		years employed	years employed	years employed
Attr. 2nd most imp.		medium risk purp	medium risk purp	insurance premium
Attr. 3rd most imp.		insurance premium	insurance premium	frequency paid

Table 10: Predicting default in first 12 months on oversampled data set.

gives the results for loan default between 12 and 24 months. Here, the neural network was superior and yielded a classification accuracy of 78.58% whereas the logistic regression classifier gave 78.24% and the Cox model 77.50%. The performance difference between the NN model and the Cox model was significant. Note that when comparing Tables 10 and 11 with Tables 8 and 9, it becomes clear that the oversampling allowed to correctly detect a higher proportion of bads as bad. Analogous to the previous subsection, we

	Actual	Logit	Cox	NN
G-predicted G	2015	1753	1744	1757
G-predicted B	0	262	271	258
B-predicted G	0	262	271	258
B-predicted B	394	132	123	136

Table 11: Predicting default 12-24 months on oversampled data set.

can also generate 3D surface plots from the neural network outputs in order to present a general view of the sensitivity of the survival probabilities with respect to the continuous inputs.

Conclusions

In this paper, we studied the use of survival analysis methods for credit scoring. Traditionally, credit scoring aimed at distinguishing good customers from bad customers. However, knowledge of the timing of when customers default or pay off early has become more and more interesting for e.g. calculating the profit over a customer's lifetime. In the literature, this problem has been typically tackled using statistical survival analysis methods such as the proportional hazards method. However, these models suffer from a number of drawbacks which have been discussed in the paper.

Being non-linear, universal approximators, neural networks may be a very attractive alternative for survival analysis modeling. Many neural network based survival analysis approaches have already been suggested in the literature. Each of them differs in the way of modeling censored observations, time-varying inputs and scalability. In this paper, we provided a literature overview of neural network approaches that have been suggested for survival analysis modeling.

In the empirical part of this paper, we compared the performance of the proportional hazards model with that of a neural network based survival analysis model on a data set of 15000 observations. We investigated when customers default as well as when they pay off their loan early. For both problems, the neural network approach did not significantly outperform the estimated proportional hazards models. If performance improvements were found, they were only marginal. Since this was only investigated on one data set, further research is needed to investigate the generality of these findings on more data. Moreover, it would also be interesting to investigate the impact of the presence of time varying inputs and penalized proportional hazards models.

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