START-UP BUSINESS SUCCESS PREDICTION BY MEANS OF ARTIFICIAL NEURAL NETWORKS

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ABSTRACT
There is a great interest to know if a new company will be able to survive or not. Investors use different tools to evaluate the survival capabilities of middle-aged companies but there is not any tool for start-up ones. Most of the tools are based on regression models and in quantitative variables. Nevertheless, qualitative variables which measure the company way of work and the manager skills can be considered as important as quantitative ones.

Develop a global regression model that includes quantitative and qualitative variables can be very complicated. In this study, a more powerful modeling tool is used to predict the company early years success. Artificial neural networks can be a very useful tool to model the company survival capabilities. They have been large specially used in engineering processes modeling, but also in economy and business modeling.

Keywords: Artificial neural networks, Enterprise solvency, Entrepreneurship success, SME

1. INTRODUCTION

Small and medium-sized enterprises are actually a country driving force, both in economic and employment creation. It is, therefore, important to promote the creation of new enterprises and ensure their survival, especially in the first critical three years of life. To do so, arise different policies for supporting of entrepreneurs, with the objectives of boosting entrepreneurship and support the birth of business initiatives by helping them in their beginnings.

In this aspect, from the point of view of the sponsoring body, is important to know which the degree of survival that can have the new company. Obtaining a model that attempts to explain the success or failure in a company from quantitative and qualitative variables is a task that currently involved numerous researchers and great efforts. Such a model would not only help emerging companies to predict the outcome, but would facilitate a great tool for detecting of possible weaknesses causing of a business failure. However, until now, these studies have focused more on set up companies than in new established firms.

These models, mainly regression ones, are based on quantitative variables as the Altman ratios and qualitative variables such as training manager, product quality, or training , innovation, price and quality control policies established in the company. However, to date, these models have not got an acceptable results to apply them to real life, mainly because of limitations in regression fits to model the relationships between the different variables involved in each case.

In the case of start-up businesses to predict survival studies are few and with very poor results.

Our study will use a new methodology in its application to start-up businesses. An artificial neural network will be developed for business success/failure of start-ups modeling based on both financial data and qualitative information relating to the various managerial policies. To obtain these data a series of personal surveys shall be carried out on behalf of the promoter team in each company, out of a total of 125. In order to unify the qualitative variables quantification is important to perform the surveys by the same team.

Artificial neural network are a type of mathematical structures that imitates the functioning of the brain. Their uses have been increased in the last years due to the high computers development. Artificial neural networks are capable of extracting knowledge from a series of sampling data and applying it later to unknown data. As a universal function aproximator has become a powerful tool in modeling. The major beneficiary has been the industrial scope with the production processes modeling, but also in the economic field have been a great development, ranging from modeling of Forex market to different products market value (Jalil and Misas, 2007) and the study of the enterprise solvency prediction (Lacher et al, 1995; Jo et al, 1997; Yang et al, 1999; Hsiao et al, 2009).

The power of artificial neural networks for modeling complex relationships between variables and the success achieved in other fields, where have surpassed traditional regression models, makes us to be optimistic about its use in this study.

This study aims to predict the degree of survival of a start-up company from their first two years of activity data and detect possible competitive weaknesses.

2. MATERIALS AND METHODS

2.1. Entrepreneurship in Spain

The Spanish entrepreneurship's basic indexes through 2009 have been affected by the economic crisis. After a moderate drop (8%) in 2008, the Total Entrepreneurial Activity index (TEA) experienced a great drop (27.1%) in 2009, returning to 2004 levels (de la Vega García 2010) (Fig 1).

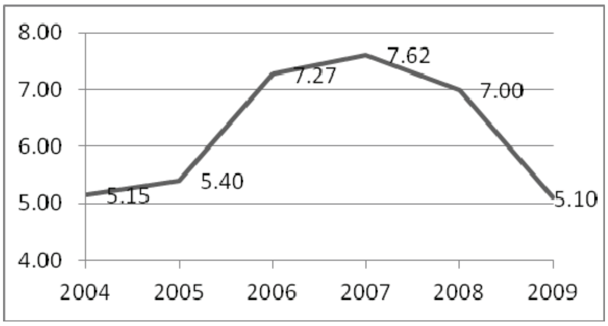

Fig.1. 2009 Executive Report. Global Entrepreneurship Monitor- Spain

According to that data, there are 1,534,964 nascent businesses (between 0 and 3 months old). The owner-managers of a new business (more than 3 months but not more than 3.5 years) have also declined in 2009, returning to 2007 levels.

As in other comparable, innovation-driven, countries, the typical early stage entrepreneur in Spain is male (62.5% of all entrepreneurs), with a mean age of 36.6, and well educated (55.4% with a university degree). The female entrepreneurial initiatives have been declined in 2009 and the difference between female and male Total Entrepreneurial Activity index (TEA) rates is now bigger than in 2008. The gender difference in the TEA index has increased from two to almost three points. Now the female TEA index is 3.33% and the male TEA index is 6.29%.

Although most individuals are pulled into entrepreneurial activity because of opportunity recognition (80.1%), others are pushed into entrepreneurship because they have no other means of making a living, or because they fear becoming unemployed in the near future. These necessity entrepreneurs are 15.8% of the entrepreneurs in Spain.

In Spain, the distribution of early-stage entrepreneurial activity and established business owner/managers by industry sector is similar to that in other innovation-driven countries, where business services (i.e., tertiary activities that target other firms as main customers, such as finance, data analysis, insurance, real estate, etc.) prevail. In Spain, they accounted for 56.5% of early-stage activities and 46.1% of established businesses. Transforming businesses (manufacturing and construction), which are typical of efficiency-driven countries, were the second largest sector, accounted for 25.9% and 24.2% respectively. Consumer services (i.e., retail, restaurants, tourism) accounted for 12.8% and 17.3%, respectively. Extraction businesses (farming, forestry, fishing, mining), which are typical of factor-driven economies, accounted for 6.0% and 8.6%, respectively. The real estate activity in Spain was of great importance, and its decline explains the reduction in the business services sector in 2009.

The median amount invested by entrepreneurs in 2009 was around 30,000 Euros (less than the median amount of 50,000 Euros in 2008). Therefore the entrepreneurial initiative is less ambitious in general.

The factors that mostly constrain entrepreneurial activity are: first, financial support (e.g., availability of debt and equity), which was cited as a constraining factor by 62% of respondents. Second, government policies supporting entrepreneurship, which was cited as a constraining factor by 40% of respondents. Third, social and cultural norms, which was cited as a constraining factor by 32% of respondents.

More than one fifth of the entrepreneurial activity (21.5%) was developed in a familiar model. Therefore, the entrepreneurial initiatives, often driven by family members, received financial support or management assistance from some family members. Nevertheless, the influence of some knowledge, technology or research result developed in the University was bigger than expected. People decided to start businesses because they used some knowledge, technology or research result developed in the University (14.3% of the nascent businesses, and 10.3% of the owner-managers of a new business).

2.2. Questionnaire

The company survival is greatly influenced by its financial capabilities, however, this numerical information is not always easy to obtain, and even when obtained, it is not always reliable.

But there are some other non numerical factors that determine company survival, such as its educational level of its employees, its customer service policies or its technical capabilities.

For this study, both numerical and qualitative data are used to model the company survival.

1.- Financial data.

Altman develop a regression model based in some financial ratios to predict the company success (Lacher et al. 1995): The most used are:

- Working Capital/Total Assets. Working Capital is defined as the difference between current assets and current liabilities. Current assets include cash, inventories, receivables and marketable securities. Current liabilities include accounts payable, short-terms provision and accrued expenses.

- Retained Earnings/Total Assets. This ratio is specially important because bankruptcy is higher for start-ups and young companies.
- Earnings Before Interest and Taxes/Total Assets. Since a company's existence is dependent on the earning power of its assets, this ratio is appropriate in failure prediction.
- Market Capitalization/Total Debts. This ratio weighs up the dimension of a company's competitive market place value.
- Sales/Total Assets. This ratio measures the firm´s assets utilization.

2.- Qualitative data.

It is very difficult to evaluate qualitative characteristics as quality policies or technical capabilities. In this study the works of Rubio Bañón and Aragón Sánchez (2002) and Aragón Sánchez and Rubio Bañón (2005) are used. They modeled the company positioning and its survival capabilities and the influence of other factors as manager personality or the educational level of its employees:

- Manager academic level, ranged from 1 to 4.
  - PhD or Master (4).
  - University degree (3).
  - High school (2).
  - Basic studies (1).
- Company technological resources, ranged from 1 to 4.
  - The company uses self-made software programs (4).
  - The company uses specific programs but it buys them (3).
  - The company uses the same software than competitor (2).
  - The company uses older software than competitors (1).
- Quality policies, ranged from 1 to 5.
  - The company has quality policies based on ISO 9000 (5).
  - The company controls either, production and client satisfaction (4).
  - A production control is the only quality policy (2).
  - Supplies control is the only quality control in the company (1).
  - The company has not any quality policy.
- Trademark, ranged from 1 to 3.
  - The company trademark is better known than competitors' (3).
  - The company trademark is as known than competitors' (2)
  - The company trademark is less known than competitors' (3).
- Employees education policy, ranged from 1 to 2.
  - The company is involved in its employees education (2).
  - The company is not involved in its employees education (1).
- Number of innovations areas in the company, ranged from 1 to 5.
- Marketing experience, ranged from 1 to 3.
  - The company has a great marketing experience in the field of its products and in others (3).
  - The company has only marketing experience in his field of duty (2).
  - The company has no marketing experience (1).
- Knowledge of the business area, ranged from 1 to 3.
  - The manager knows perfectly the business area and has been working on several companies related whit it (3).
  - The manager knows lightly the business area (2).
  - The manager has no idea on the business area (1).
- Openness to experience, ranged from 1 to 2.
  - The manager is a practical person who is not interested in abstract ideas, prefers works that is routine and has few artistic interest (2).
  - The manager spends time reflecting on things, has an active imagination and likes to think up new ways of doing things, but may lack pragmatism (1).

Table 1. Variables

Variable	Type	Range
Working Capital/Total Assets	Quantitative	R^+
Retained Earnings/Total Assets	Quantitative	R^+
Earnings Before Interest and Taxes/Total Assets	Quantitative	R^+
Market Capitalization/Total Debts	Quantitative	R^+
Sales/Total Assets	Quantitative	R^+
Manager academic level	Qualitative	1-4
Company technological resources	Qualitative	1-4
Quality policies	Qualitative	1-5
Trademark	Qualitative	1-3
Employees education policy	Qualitative	1-2
Number of innovations areas	Qualitative	1-5

Marketing experience	Qualitative	1-3
Knowledge of the business area	Qualitative	1-3
Openness to experience	Qualitative	1-2

2.3. Artificial neural networks

ANN have been widely used in many engineering fields, especially when the relation between the variables involved in the process is not so important as find a suitable solution to our problem. From that point of view, ANNs have become a very important tool to model specially industrial processes, but also others kind of complex processes such as environmental changes, climate, tress growing, financial markets or traffic flow.

ANNs are a complex mathematical structures that try to imitate a biological brain and its way of thinking. They are able to learn from a series of examples and apply that knowledge to unknown situations.

These structures have a series of interconnected elements, (Fig 3) known as artificial neurons and those connections are the responsible of the knowledge storing.

One of the type of ANN most used is the perceptron (Fig. 3). It is made up of three layers, known as input layer, hidden layer and output layer. The input layer receives the initial values of the variables, the output layer shows the final results of the network for the input, and the hidden layer makes all the operations to get the final results.

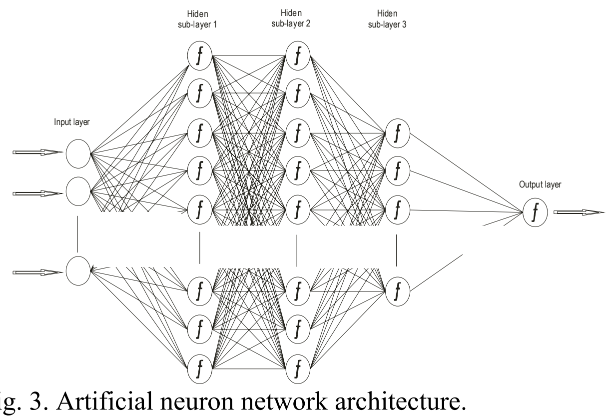

Fig. 3. Artificial neuron network architecture.

The number of neurons in the input layer is the same as independent variables, and the number of neurons in the output layer is the same as dependent variables, but, there is not a procedure to define the number of neurons and the number of layers the hidden layer should have, that means it is very difficult to choose a model, even for an experienced user. In general, the model is obtained by a trial and error process. There are some general recommendations about the final structure as it must be a pyramidal type or about the maximum number of neurons as a function of the number of examples, but they are only recommendations not really rules.

Their main advantages are they are universal non-lineal function aproximators (Hornik 1989), and perceptrons are able to filter the data noise. Data are not need to be in a normal distribution as in other statistical models. Their principal disadvantages are that they need a large amount of data for the training process, and the final model is a non interpretable model, is such a black box, where you do not know how variables are connected one to each other.

The hyperbolic tangent sigmoid function (Eq. 1) was used as the transfer function. This is equivalent to the hyperbolic tangent function and also improves network performance by producing an output more quickly (Demuth et al 2002). To improve the ANN results all the data were normalized according to Eq. 2. The transfer function produces an output in the interval (-1,+1), which means that data normalization is highly appropriate for improving network performance.

$$f(\theta) = \frac{2}{1+e^{(-2\theta)}} - 1 \qquad (1)$$

f(θ): Output value of the neuron.
θ: Input value of the neuron.

$$\theta' = \frac{\theta - \theta_{\min}}{\theta_{\max} - \theta_{\min}} \qquad (2)$$

θ': Value after normalization of vector X.
θmax y θmin: Maximum and minimum values of vector X.

The training method chosen was supervised learning. In order to this the whole initial data set has been divided into three subsets at random without repetition. The training set (60% of the data), test set (20% of the data) and validation set (20% of the data).

To avoid the problem of overfitting during the training phase, the early-stopping technique has been used. Overfitting occurs when the error in the validation set stats to increase while decreases in the training set, it is a clear indication of a generalizing loose capacity. To prevent this situation and design the ANN structure, a specific program has been develop using the Neural Network Toolbox® ver. 4.0.2, from the MATLAB® Program Ver. 6.5.0. Release 13. This program generates different perceptrons with different neurons in their inner layers, compares the training error and validation error every 100 training epochs and also compares all the preceptrons generated between them.

3. RESULTS AND CONCLUSIONS

This work is the initial steps of an ambitious project that pretend to evaluate the survival of start-up companies. Actually the work is on his second stage which is the data recompilation through different individual surveys. We hope to present in the next congress the first results to discuss them.

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