Chapter 12

Use of Artificial Neural Networks to Predict The Business Success or Failure of Start-Up Firms

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1. Introduction

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 case 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, and there is no problem in mix quantitative and qualitative variables in the same model. This kind of nets are called mixed artificial neural networks.

2. Materials and methods

2.1. A snapshot of entrepreneurship in Spain in 2009

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 ([1]de la Vega García, 2010) (Fig 1).

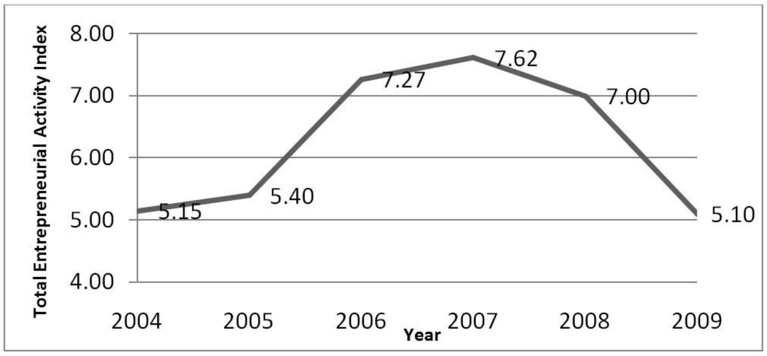

Figure 1. Executive Report. Global Entrepreneurship Monitor- Spain.

This rate implies that in our country 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

It is clear that 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.

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

Table 1. Variables

There are some other qualitative factors that have influence in the company success, such as its technological capabilities, quality policies or academic level of its employees and manager.

In this study we will use both numerical and qualitative data to model the company survival (Table 1).

2.2.1. Financial data.

The most used ratios to predict the company success are the Altman ratios ([2]Lacher et al., 1995; [3]Atiya, 2001):

• 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.

2.2.2. Qualitative data.

The election on which qualitative data should be used is based on previous works as in references [4-6] Aragon Sánchez y Rubio Bañón (2002 y 2005) and Woods and Hampson (2005), where they establish several parameters to value the company positioning and its survival capabilities and the influence of manager personality in the company survival.

- 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).

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- Supplies control is the only quality control in the company (1).
- o 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).

Researchers will conduct these surveys with managers from 125 companies. The surveys will be conducted by the same team of researchers to ensure the consistency of questions involving qualitative variables.

2.3. Artificial neural networks

Predictive models based on artificial neural networks have been widely used in different knowledge areas, including economy and bankruptcy prediction ([2, 7-9]Lacher et al, 1995;

Jo et al, 1997; Yang et al, 1999; Hsiao et al, 2009) and forecast markets evolution ([10]Jalil and Misas, 2007).

Artificial neural networks are mathematical structures based on biological brains, which are capable of extract knowledge from a set of examples ([11] Perez and Martin, 2003). They are made up of a series of interconnected elements called neurons (Fig. 2), and knowledge is set in the connections between neurons ([12] Priore et al, 2002).

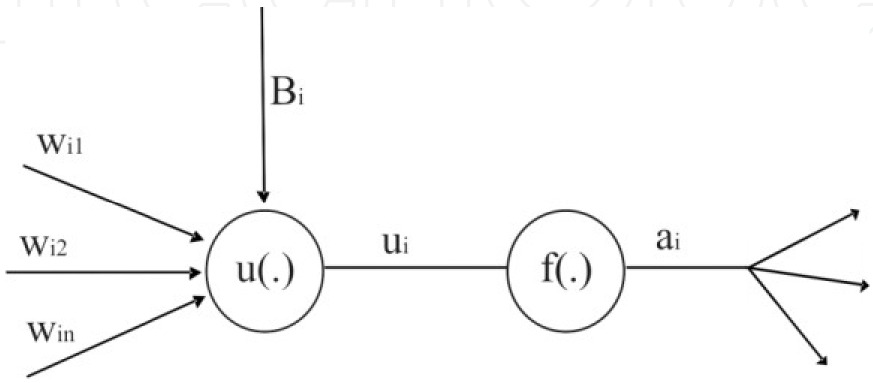

Figure 2. An artificial neuron. u(.): net function, f(.): transfer function, w_{ij}: connection weighs, B_i: Bias.

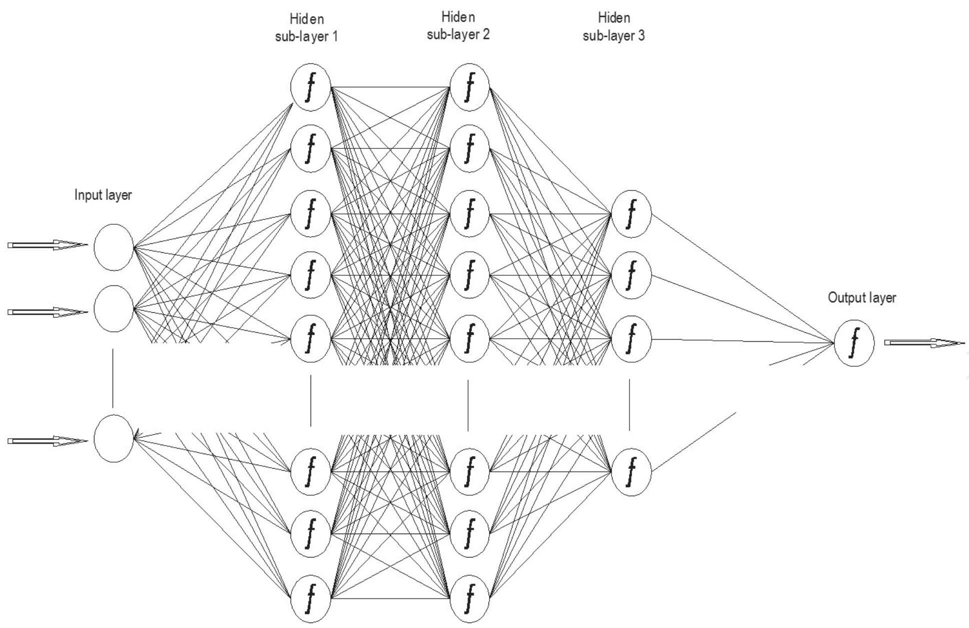

Figure 3. Artificial neuron network architecture.

Those neurons are organized in a series of layers (Fig. 3). The input layer receives the values from the example variables, the inner layer performs the mathematical operations to obtain the proper response which is shown by the output layer.

There is not a clear method to know how many hidden layers on how many neurons an artificial neural network must have, so the only method to perform the best net is by trial and error ([13]Lin and Tseng, 2000). In this work a special software will be develop, in order to find the optimum number of neurons and hidden layers.

There are lots of different types of artificial neural network structures, depending on the problem to solve or to model. In this work perceptron structure has been chosen. Perceptron is one of the most used artificial neural network and its capability of universal function aproximator ([14]Hornik, 1989) makes it suitable for modeling too many different kinds of variable relationships, specially when it is more important to obtain a reliable solution than to know how are the relations between the variables.

The hyperbolic tangent sigmoid function (Fig. 4) has been chosen as transfer function. This function is a variation of the hyperbolic tangent ([15] Chen, 1995) but the first one is quicker and improves the network efficiency ([16] Demuth et al, 2002).

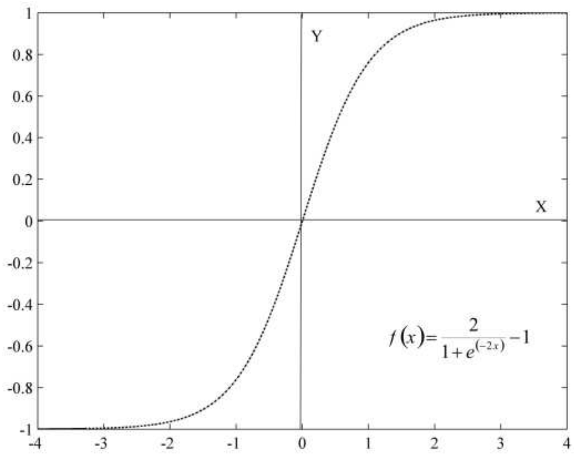

Figure 4. Tansig function. f(x): Neuron output, x: Neuron input.

As the transfer function output interval is (-1, 1) the input data were normalized before training the network by means of equation: (Ec.1) ([16-18]Krauss et al, 1997; Demuth et al, 2002, Peng et al, 2007).

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

X': Value after normalization of vector X. X_{min} and X_{max}: Maximum and minimum values of vector X.

The network training will be carried out by means of supervised learning ([11, 19-21] Hagan et al., 1995; [20] Haykin, 1998; [11] Pérez & Martín, 2003; [21] Isasi & Galván, 2004). The whole data will be randomly divided into three groups with no repetition. The training set (60% of the data), test set (20% of the data) and validation set (20% of the data).

The resilient backpropagation training method will be used for training. This method is very adequate when sigmoid transfer functions are used ([16] Demuth et al, 2002).

To prevent overfitting, a very common problem during training, the training set error and the validation set error will be compared every 100 epochs. Training will be considered to be finished when training set error begins to decreases while validation set error increases.

As mentioned before, to find the optimum artificial neural network architecture an specific software will be develop. This software makes automatically different artificial neural network structures with different number of neurons and hidden layers. Finally the software will compare the results between all the nets developed and will choose the best one. (Fig. 5, 6)

```
Initilize_data
Preprocessing_data
// Sublayer loops
for h=1 to 15
for i=1 to h
Create_neural_network (net)
// Training loop
for k=1 to 500
Train(net)
Simulate(net)
Avoid_overfitting
end for //k
end for //i
end for //h
// Final
Get_best_net
Display_results
...
```

Figure 5. Program pseudocode.

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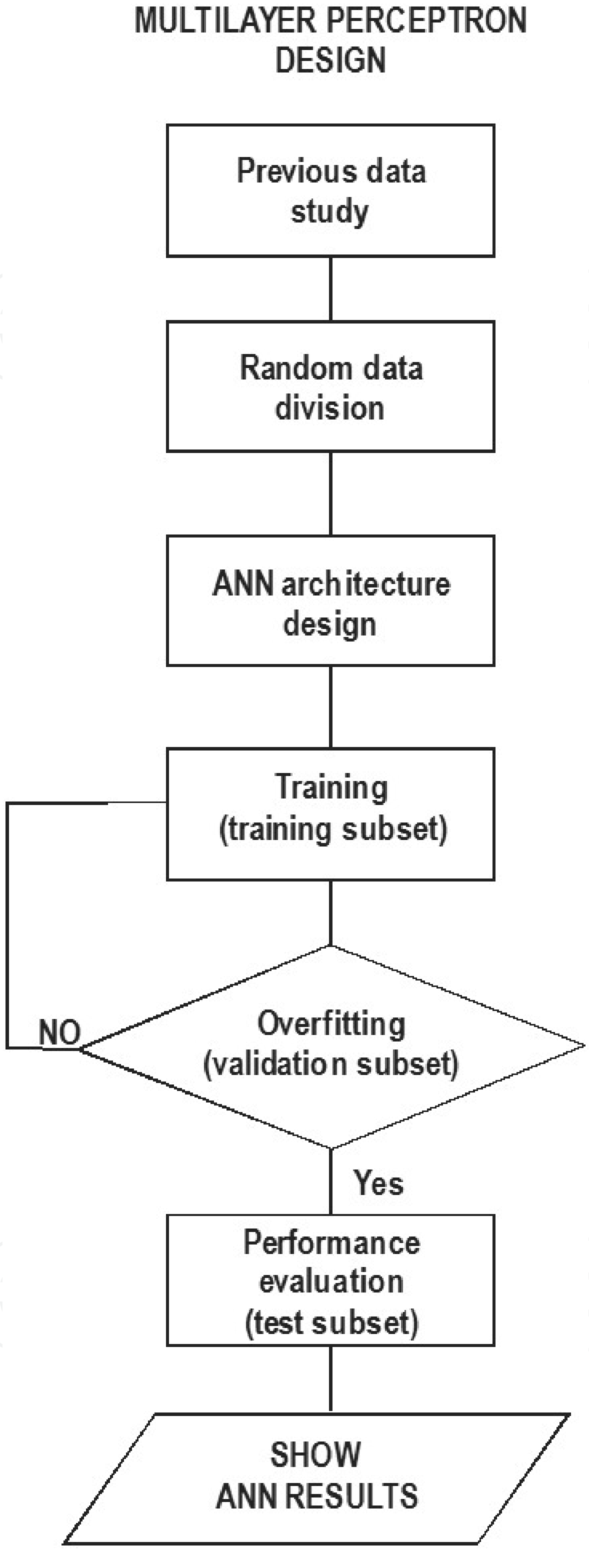

Figure 6. Neural network design flow chart.

The Matlab Artificial Neural Network Toolbox V.4. will be used for develop the artificial neural network.

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 third stage which is the data analysis by means of artificial neural network modeling method.

Once finished it is expected to have a very useful tool to predict the business success or failure of start-up firms.

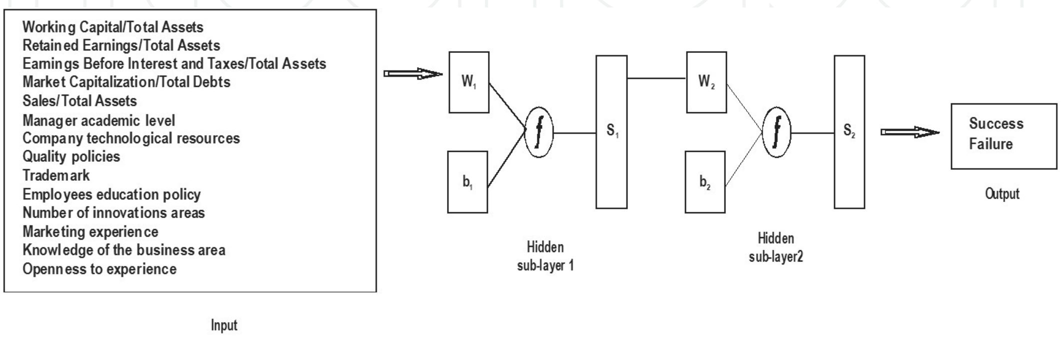

Figure 7. Most expected neural network architecture.

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